Consumer, Marketing, AI: Dark Sides and Ethics

Editors: Kürşad Özkaynar • Şevin Abbasoğlu

ÖZGÜR PRESS

Consumer, Marketing, AI: Dark Sides and Ethics

Editors:

Kürşad Özkaynar

Şevin Abbasoğlu

ÖZGÜR PRESS

Published by
Özgür Yayın-Dağıtım Co. Ltd.
Certificate Number: 45503

15 Temmuz Mah. 148136. Sk. No: 9 Şehitkamil/Gaziantep
+90.850 260 09 97
+90.532 289 82 15
www.ozguryayınlari.com
info@ozguryayinlari.com

Consumer, Marketing, AI: Dark Sides and Ethics
Editors: Kürşad Özkaynar • Şevin Abbasoğlu

Language: English
Publication Date: 2025
Cover design by Mehmet Çakır
Cover design and image licensed under CC BY-NC 4.0
Print and digital versions typeset by Çizgi Medya Co. Ltd.

ISBN (PDF): 978-625-5958-72-3

DOI: https://doi.org/10.58830/ozgur.pub710

Suggested citation:
Özkaynar, K. (ed), Abbasoğlu, Ş. (ed) (2025). *Consumer, Marketing, AI: Dark Sides and Ethics.* Özgür Publications. DOI: https://doi.org/10.58830/ozgur.pub710. License: CC-BY-NC 4.0

The full text of this book has been peer-reviewed to ensure high academic standards. For full review policies, see https://www.ozguryayinlari.com/

ÖZGÜR PRESS

Preface

In the 21st century digital age, artificial intelligence (AI) technologies are a technical revolution and a paradigm shift leading to transformations in a wide range of areas, from consumption practices to ethical norms, from individual preferences to social structure. This book examines the effects of artificial intelligence in the context of marketing and consumer behaviour in a multidimensional manner and evaluates both opportunities and threats from an academic perspective.

Each chapter focuses on different aspects of AI and provides in-depth analyses with an interdisciplinary approach. From approaches that discuss how consumer autonomy is being eroded to ethical dilemmas encountered in AI-supported advertising, from the effects of unrealistic beauty ideals on individuals' self-perception to algorithmic manipulations and fake evaluation systems, many topics are comprehensively covered.

Understanding how AI affects individuals' decision-making processes is critical for marketing strategies and consumer welfare, ethical design principles, and digital rights. Therefore, the book's main aim is to go beyond the possibilities offered by AI-enabled systems to assess the cognitive, emotional and behavioural effects caused by these technologies and propose constructive solutions for decision-makers, practitioners and academics.

The studies presented in our book deal in depth with current and controversial topics such as marketing ethics, neuro-marketing, algorithmic decision-making, the impact of artificial intelligence on creative processes, dark patterns and fake user reviews. Each chapter combines theoretical frameworks with empirical findings to give the reader an intellectual grounding and practical implications.

This book aims to be an important reference source for all academics, researchers, and professionals who are aware of the new dynamics driving consumer behaviour in a digitalised world, think critically, and are ethically sensitive. In this period shaping the future of artificial intelligence, it is a common call to build a human-centred and sustainable digital consumption culture that prioritises ethical responsibility.

Contents

Chapter 1

Overcoming the Dark Sides of Artificial Intelligence

Şevin Abbasoğlu[1]

Abstract

This chapter explores the development, classification, and application of artificial intelligence (AI), with a particular focus on its ethical implications and the so-called "dark sides." It outlines different types of AI—such as weak, general, and super AI—and their levels of autonomy, emphasizing the extent to which human intelligence can be mimicked. The chapter examines how AI technologies, especially in the field of marketing, enhance customer experiences through personalized recommendations, while simultaneously raising concerns regarding data privacy, manipulation, and unethical practices like fake reviews. It argues that sustainable marketing requires building customer trust by adhering to ethical principles, including transparency, informed consent, and legal compliance. The discussion concludes that overcoming the dark sides of AI will enable businesses to establish long-term customer relationships, foster brand loyalty, and create greater brand value through ethical, value-driven AI applications.

The Dark Side of Artificial Intelligence

Artificial intelligence is defined as imitated human intelligence that does not have to be limited by biologically observable methods (McCarthy, 2007:2). Artificial intelligence, which is related to the simulation, expansion and dissemination of human intelligence, is considered as a sub-field of computer systems (Shi and Zheng, 2006:810). The world of the 21st century, guided by technological developments, has created the concept of artificial intelligence by imitating human intelligence, and artificial intelligence has become one of the important elements of daily life thanks to its advanced memory and data processing ability.

1 Dr. Öğr. Üyesi, Sivas Cumhuriyet Üniversitesi Zara Veysel Dursun Uygulamalı Bilimler Yüksek Okulu, e-Mail: sevinabbasoglu@hotmail.com, ORCID ID: 0000-0001-9269-8298

https://doi.org/10.58830/ozgur.pub710.c3018

According to Morandin Ahuerma (2022:1948), there are different types of artificial intelligence. Based on their cognitive aspects, they are classified into three types: weak or limited artificial intelligence, general or strong artificial intelligence (AGI), super artificial intelligence (ASI), and according to their autonomy, they are classified into four types: reactive artificial intelligence, thinking artificial intelligence, cognitive artificial intelligence and autonomous artificial intelligence. Weak or limited artificial intelligence is a system that can perform specific actions quite well, while strong artificial intelligence is a system that can think like a human, imitate common sense and empathy based on general knowledge (Sterne, 2017:10; Binbir, 2021:317). Super artificial intelligence is also called high-performance artificial intelligence. Although it fulfills all tasks that require human intelligence, it has the ability to surpass humans in terms of cognitive and learning abilities (Tzimas, 2021; Morandín-Ahuerma, 2022:1949). Reactive artificial intelligence is the type that produces an output depending on the input it receives. As long as the input remains the same, the action will remain constant. Examples include spam filters and Netflix recommendation engine (https://bernardmarr.com/what-are-the-four-types-of-ai/). Cognitive artificial intelligence is a type of artificial intelligence that imitates human intelligence by thinking and trying to learn (https://www.cohesity.com/glossary/cognitive-ai/). Autonomous artificial intelligence is a type of artificial intelligence that can interact with its environment spontaneously, without any intervention, make decisions and set goals and strategies based on new drums (Mathews at all., 2021:4).The increase and development of types of artificial intelligence reveals the fact that human intelligence can be imitated in every aspect.This reality shows that technology can replace humans in many areas, that many algorithms can think and work like humans, and that it can be used for good purposes as well as for bad purposes.The increase and development of types of artificial intelligence reveals the fact that human intelligence can be imitated in every aspect.

Artificial intelligence, which develops with the opportunities offered by developing technology, is present in many segments in the field of marketing as in many fields. Artificial intelligence technology is actively used in different business areas and sectoral activities. While artificial intelligence technologies, which can perform transactions through databases, provide great advantages to businesses, they are thought to have negative effects on customers in terms of data privacy and ethics. The dark side of artificial intelligence has emerged with the manipulation of customers by profit-making applications, especially for businesses operating in the field of marketing. In the 21st century technology era, where online shopping is more preferred, it has been observed that customers are active on online shopping sites for a long time. During this period, customers who are exposed to advertisements of various products and services evaluate the activities of businesses' artificial intelligence applications, which they define as the art of influencing customers, as manipulation when evaluated from the customer's perspective. Different practices such as fake reviews in the evaluation tabs of the products, customers identified by businesses that make evaluations as if they have used the product, extra stars, etc. are not ethically appropriate and reveal the dark side of artificial intelligence.The basic ethical values of artificial intelligence include ensuring that customers use this technology and its extensions without prejudice.The main purpose of the studies on the protection of personal data is to protect customer rights.The fact that personal data can be processed and shared with third parties negatively affects the ethical dimension of artificial intelligence-oriented strategies.The values that businesses are expected to offer to customers at this point are openness and clarity, paying attention to ethical elements, processing data at a minimum level and customer approval in this process.

Based on the understanding of sustainable marketing, which is becoming increasingly important in the current century, the basic condition for using artificial intelligence as a long-term reliable marketing tool is to provide the necessary customer trust. The basis of marketing strategies is to convince customers to sell. The formation of purchase intention in customers, even if the purchase behavior does not occur, is an important factor for businesses that brings the potential customer one step closer to the business. With the increasing use and impact of artificial intelligence, traditional methods have taken a back seat. Although this is an advantageous situation, with the increase in data processing and the effect of manipulations created due to the increase in data processing, customers are quickly directed to sales with a faster and fuzzy decision-making. The rapid progression of the neurological influence process seems to neutralize the decision-making independence of customers. It is inevitable that customers who want to make informed decisions and do not want to be manipulated in line with the principle of ethics and transparency should have more knowledge in this field. While customers are expected to improve their digital literacy and protect themselves, businesses need to ensure the prerequisite of creating customer value by taking legal regulations into account. In addition to all these, the regulation of dark parties with legal practices and the establishment of ethical standards and the implementation of sanctions constitute the basis of sustainable marketing.

For businesses, overcoming the dark sides will create long-term customer relationships, increase brand value and build brand loyalty.

Considering that the positive energy emitted by satisfied customers is more effective in influencing other customers than many promotional activities, the importance of using artificial intelligence technologies with ethical standards is quite clear. In this sense, businesses can offer suggestions such as identifying and correcting the deficiencies in negative comments made by online shopping platforms instead of positive comments made through fake accounts, increasing the quality of the products and services offered instead of constantly bombarding customers with messages and advertisements throughout the day, engaging in activities that support customers' healthy decision-making processes instead of serving personal data in inappropriate ways, developing marketing strategies that create customer value within the scope of openness, transparency and ethical values, and creating systems integrated with artificial intelligence.

Kaynakça

Binbir, S. (2021). Pazarlama Çalışmalarında Yapay Zeka Kullanımı Üzerine Betimleyici Bir Çalışma, Yeni Medya Elektronik Dergisi, 5 (3), 314-328

Matthews, G., Hancock, P. A., Lin, J., Panganiban, A. R., Reinerman-Jones, L. E., Szalma, J. L., & Wohleber, R. W. (2021). Evolution and revolution: Personality research for the coming world of robots, artificial intelligence, and autonomous systems. *Personality and individual differences, 169*, 109969.

McCarthy, J. (2007). What is artificial intelligence.

Morandin- Aurherma F., (2022). What is artificial intelligence. *International Journal of Research Publication and Reviews*, *Vol:3,* No:2, pp.1947-1951.

Shi, Z. Z., & Zheng, N. N. (2006). Progress and challenge of artificial intelligence. *Journal of computer science and technology*, *21*(5), 810-822.

Sterne, J. (2017). Artificial intelligence for marketing: practical applications. *John Wiley & Sons.*

Tzimas, T. (2021). Legal and Ethical Challenges of Artificial Intelligence froman International Law Perspective *(Springer, Ed.)*. https://doi.org/10.1007/978-3-030- 78585-7.

İNTERNET KAYNAKLARI

https://bernardmarr.com/what-are-the-four-types-of-ai/

https://www.cohesity.com/glossary/cognitive-ai/

Chapter 2

Algorithmic Manipulation: Influencing Consumer Behavior

" if you're not paying for the product, then you are the product. "

Andrew Lewis

Zeynep Erdoğan[1]

Esen Gürbüz[2]

Abstract

Andrew Lewis's quote, "If you are not paying for the product, you are the product," summarizes the functioning of digital platforms. YouTube (excluding premium membership) and similar social media platforms provide free services to users while collecting user data to feed their algorithms and enhance engagement through personalized content and targeted advertising strategies (Iena, 2023:838-839). In this context, although users do not make direct payments, the revenue model is fundamentally based on extending the time spent on the platform.

Algorithms, combined with technologies such as artificial intelligence, machine learning, and deep learning, offer businesses the opportunity to analyze consumer behavior and personalize marketing strategies. However, these technologies are not only innovative tools but also have an aspect that includes ethical issues and manipulative effects. The algorithms behind digital technology, for instance, analyze users' interests to keep them on the platform longer while also giving them the feeling of "missing out," thereby influencing purchasing behavior. Furthermore, presenting content based on users' emotional states, violations of data privacy, and elements of psychological pressure bring the ethical dimension of algorithmic manipulation into

1 Research Assistant, Niğde Ömer Halisdemir University, Faculty of Economics and Administrative Sciences, Department of Business Administration, Department of Production Management and Marketing, zeyneperdogan@ohu.edu.tr, 0000-0003-1712-3114

2 Prof. Dr., Niğde Ömer Halisdemir University, Faculty of Economics and Administrative Sciences, Department of Business Administration, Department of Production Management and Marketing, esen@ohu.edu.tr, 0000-0001-5156-1439

https://doi.org/10.58830/ozgur.pub710.c3019

question.This study explains the theoretical foundations of algorithmic manipulation, its potential negative effects on consumer autonomy, and its capacity to influence consumer behavior.

1. Introduction

Algorithms, rooted in the field of mathematics, have been developed to solve specific problems by utilizing mathematical logic and procedural steps (Sayılı & Dosay, 1991:102; Finn, 2017:17; Miyazaki, 2012; wikipedia.org/03.01.2025). An algorithm is a procedure consisting of systematically defined and ordered instructions designed to solve a particular problem or perform a specific task. Algorithms take a given input, process it systematically, and produce the desired output (Önder, 2024; Chaudhuri, 2020:2). According to Google's definition, algorithms are mechanisms that analyze users' queries through computational processes and formulas, transforming them into meaningful answers (Finn, 2017:18). More generally, an algorithm is a systematic method that processes input values according to a specific logical framework and transforms them into output values. While the problem definition identifies the intended output and the corresponding input-output relationship, the algorithm clearly and explicitly describes the steps to achieve this goal. In other words, an algorithm is a structured set of instructions designed to solve a specific problem (Cormen et al., 2009:5; Miyazaki, 2012; Chaudhuri, 2020:2; Altun, 2018:38).

The term "algorithm" originates from the medieval Western European term "algorismi" or "algoritmi," which referred to the calculation method performed using Hindu-Arabic numerals. Various forms of this term, derived from the name of the mathematician Al-Khwarizmi, laid the foundation for the modern concept of the "algorithm" as a specific computational method. It is suggested that mathematical calculation methods were introduced to Western Europe through Al-Khwarizmi's works, ultimately leading to the emergence of the term "algorithm" (Sayılı & Dosay, 1991:102; Finn, 2017:17; Miyazaki, 2012; wikipedia.org/03.01.2025; Üngör et al., 2020:99). Based on the historical relationship between Al-Khwarizmi and algorithms, the Turkish Ministry of National Education has implemented the Khwarizmi Education Model to equip students with algorithmic thinking and problem-solving skills (harezmi.meb.gov.tr/03.01.2025; Coşkun Keskin et al., 2023:259).

Algorithms are clearly rooted in the field of mathematics, making it important to note that algorithms existed even before the emergence of computer science (Finn, 2017:17). However, the advancement of computer science and technology has facilitated the development of a greater number of algorithms (Cormen et al., 2009:14). Mathematical thinking processes and systematic problem-solving methods have been employed across various disciplines throughout history. With the development of computer science, algorithms have become more distinct and structured. Algorithms are at the core of computer science. Many of the technologies used in modern computers are built upon algorithms (Cormen et al., 2009:14). Algorithms serve as the mechanisms underlying numerous technologies, enabling systems to operate faster, more efficiently, and more intelligently (Shekhar et al., 2018:674). Additionally, algorithms are defined as systems that develop effective strategies by providing solution-oriented steps when encountering any issue or problem (Özkök, 2019:14).

Technologies such as artificial intelligence, machine learning, and big data analytics enhance the accuracy and functionality of algorithms, facilitating the lives of both businesses and individuals (Arıcan Kaygusuz, 2023:534). In this context, machine learning, a subfield of artificial intelligence, has gained significant popularity in recent years, with many technology companies achieving remarkable advancements through algorithms in this domain. For instance, digital platforms like Netflix utilize machine learning algorithms to analyze users' past viewing habits and provide personalized content recommendations (Shekhar et al., 2018:674). Particularly, "deep learning" stands out as a branch of artificial intelligence that offers significant innovations in areas such as speech recognition, personal assistants, image recognition, and security camera analyses. These algorithms, which possess the ability to learn at a speed comparable to human perception, are referred to as "deep learning" (Arıcan Kaygusuz, 2023:534).

In addition to their robust infrastructure and numerous advantages, algorithms also have ethically and socially controversial aspects (Kayıhan et al., 2021:296). It is argued that algorithms are not only tools used to solve problems and facilitate human life but are also employed to manipulate users' data (Finn, 2017:17). With technological advancements, ethical issues related to algorithms have been observed to increase. For instance, algorithms can sometimes lead to ethical concerns such as misinformation, violations of data privacy, or the creation of discrimination. This situation indicates that algorithms can be viewed not only as tools for beneficial purposes but also as instruments carrying the risk of misuse. Therefore, adhering to ethical and transparency principles is crucial during the development and application of algorithms (Kayıhan et al., 2021:296).

Etymologically, the term "manipulation," meaning "to operate" and "to use" (Özkök, 2019:14), refers to the process of altering information through selection, addition, or removal (Fırat, 2008:22-23). The concept of manipulation has been addressed from various perspectives across different disciplines and is generally defined as the process of misleading and directing an event, situation, or individuals (Eryılmaz, 1999:21; Altuncu, 2013:116).

An important aspect of manipulation involves influencing an individual without fully engaging their rational faculties (Sunstein, 2016, cited in Christiano, 2022:110). According to Ergül Güvendi (2023:57), manipulation is related to the psychological and social effects consciously applied by one individual to influence, direct, and alter the behavior of another individual against their will. According to Atan et al. (2013:2), manipulation is the reorganization of data in accordance with a specific intention, involving the use of misleading methods in the process.

Algorithms operate as a series of step-by-step procedures or commands executed to achieve a specific goal. In this process, they determine how to proceed to reach the defined objective and ensure that these actions are carried out in a particular sequence (Goffey, 2008, cited in Witzenberger, 2017:17). Algorithms perform functions such as analyzing user behavior, providing content and recommendations based on personal preferences, guiding individuals or groups toward specific ideas, shaping public opinion, and delivering content based on emotional states. However, it should be considered that during the stages of data collection and processing, these processes may lead to conscious or unconscious manipulations of users.

Manipulation refers to the deliberate intervention in the message structure and content between the sender and the receiver. This intervention is typically carried out by the source of the message or through specific tools, and it affects the cognitive processes of the receiver, influencing them to generate desired thoughts and ideas, with the aim of changing or directing individuals' thoughts for various purposes (Elitaş, 2022:115). Particularly, the functionalization of data-driven marketing activities indicates that an approach centered on the consumer, with the primary goal of influencing them, has been adopted. In this context, algorithms play a critical role in marketing processes (Karaman, 2021:1341-1344). While consumer manipulation was previously carried out through traditional communication channels, with the widespread use of digital environments today, this process is also conducted through digital channels. The spread of deceptive content in digital and internet environments, the exploitation of individuals' vulnerabilities, social media addiction, social isolation, digital harassment, data privacy violations, and unethical practices such as guiding individuals through manipulative methods are becoming increasingly significant issues

(Şen, 2024:18). In this context, it should not be overlooked that algorithms are not only tools that improve user experience but also mechanisms that direct and even manipulate individual behaviors. In this regard, the widespread use of algorithmic manipulation and the magnitude of its effects are critical issues that must be considered. This section explains the potential of algorithms to influence consumer behaviors through data manipulation.

2. Algorithmic Manipulation and Its Theoretical Foundations

Algorithms are fundamental elements that determine the operation of digital systems and infrastructures. They not only guide the operation of a single software or device but also form the foundation of a wide technological system, including the internet, mobile devices, digital services, and network infrastructures (Kitchin, 2014:11; Karaman, 2021:1341). Algorithms are powerful tools that are rapidly evolving and integrated into many different areas of our lives today (Finn, 2017:15; Witzenberger, 2017:25). Algorithms not only regulate the operation of technical systems but also form the foundation of technological processes that have deep impacts on daily life (Kitchin, 2014:11; Karaman, 2021:1341). On digital platforms, manipulation strategies of algorithms are referred to as "algorithmic manipulation." This manipulation strategy processes user data to direct individuals toward specific behaviors (Vangeli, 2023:15). The effect of manipulative messages prevents individuals from making rational evaluations within the information pollution (Elitaş, 2022:116).

Manipulation is a type of psychological influence that shapes people's behaviors and thoughts, targeting social consciousness. Directing individuals to perform certain actions unconsciously and creating a socio-psychological control mechanism that is difficult to notice by the target audience are among the core functions of manipulation (Rohach & Rohach, 2021:47). Algorithmic manipulation becomes more complex and problematic as online algorithms are trained with more personalized user data. Algorithms are fed with users' health status, age, past experiences, and other personal data; they use this information to better predict and guide user behaviors (Vangeli, 2023:15). The prominent aspect of algorithmic manipulation is the amount of data that algorithms can process, the accuracy of targeting individuals, and the ability to calculate and continuously update all these processes at high speed (Christiano, 2022:115).

Algorithms have powerful functions such as controlling the flow of information, shaping user behaviors, and influencing social processes (Witzenberger, 2017:18). Hypernudging is a strategy that attempts to influence individuals' decisions by presenting relationships and connections determined by algorithms to users (Rickert, 2024:424). Hypernudging enables algorithms to dynamically restructure the guidance process based on the data they receive. In this process, algorithms are updated according to individuals' current behaviors and previous interactions, providing personalized guidance (Christiano, 2022:115).

Recommendation algorithms, as part of recommendation systems, work by analyzing data such as users' past behaviors, preferences, and profiles to predict whether they will like a specific product or content (Isinkaye et al., 2015:262). Persuasion algorithms, on the other hand, are systems designed to encourage individuals to adopt a specific behavior change (Albers et al., 2022:2). These types of algorithms are strategically used to influence users' decisions and guide them toward a specific goal (Karaman, 2021:1341).

3. Areas of Application and Behavioral Effects of Algorithmic Manipulation

Algorithms use data to perform analysis, make accurate predictions, and contribute to the efficient operation of processes in order to achieve a specific goal (Witzenberger, 2017: 24-25). With advancements in computer science, algorithms are no longer limited to academic or technical fields; they are also finding widespread application in the business world (Karaman, 2021:1341). The fact that algorithms are indifferent to ethical and moral values in social interactions and fail to adhere to ethical rules while managing human social relationships and interactions is noted as a significant issue. This indifference can lead to algorithms influencing people in a manipulative manner (Vangeli, 2023:13).

The power of algorithms has become more visible, particularly in fields such as digital media, artificial intelligence, data analytics, and social media (Witzenberger, 2017:18; Saurwein & Spencer-Smit, 2021:223). Individuals are continuously interacting with structures shaped by algorithms at every stage of their daily lives in the digital world, from online dating to route navigation, information searching to shopping (Striphas, 2015, cited in Witzenberger, 2017:17).

Every online action of users is added to the data set, allowing algorithms to use this data to develop strategies for more accurately predicting and influencing individuals' behaviors (Vangeli, 2023:15). For example, when a user wants to purchase a book online, the system analyzes their behavior in detail. All interactions, such as the products the user has viewed, purchased, or added and removed from the cart, are recorded, and these data are compared with the behaviors of other users with similar interests. As a result, the algorithms created from this process offer personalized recommendations, helping to understand user behavior (Özkök, 2019:9-10) and shaping the user experience.

Algorithms are used in various fields, ranging from stock market transactions (such as investment decisions and trading strategies) to music composition (such as creating lyrics and melodies), from autonomous vehicles to writing news articles (Finn, 2017:15). With these developments, technological advancements and digitalization also significantly expand areas susceptible to manipulation (Atan et al., 2013:2). This situation brings with it the foreseeable risk of increased manipulation through widely used algorithms.

Algorithmic manipulation, unlike traditional manipulation techniques, offers more systematic and targeted interventions by utilizing big data and artificial intelligence systems (Vangeli, 2023:13). In this regard, manipulations can be carried out by companies and other organizations in various environments and contexts, for different purposes (Ljubičić & Vukasović, 2023:11).

Algorithms encompass a wide range of disciplines (Witzenberger, 2017:25). Manipulation, on the other hand, is a phenomenon that is commonly encountered across different disciplines and various application areas (Begtimur, 2022:10). A review of the literature reveals not only the concept of algorithmic/algorithm manipulation (Fletcher, 2021; Galli, 2022; Vangeli, 2023; Fu & Sun, 2024), but also the manipulation concept being addressed in different contexts: digital manipulation (Reaves et al., 2004; Singh et al., 2024; Mucundorfeanu et al., 2024; Elitaş, 2022), market manipulation (Putni□š, 2012; Li et al., 2024), digital market manipulation (Calo, 2013; Greiss, 2021), marketing manipulation (Ljubičić & Vukasović, 2023; Jiaying & Lasi, 2023), consumer manipulation (Witte, 2023; Li & Li, 2023; Reuille-Dupont, 2023; Quinelato, 2024), online manipulation (Susser et al., 2019; Susser et al., 2019a; Boldyreva et al., 2018; Botes, 2023), social media manipulation (Bastos, 2024; Maathuis & Kerkhof, 2023; Maathuis & Godschalk, 2023), FoMO (fear of missing out) manipulation (Tan et al., 2024; McKee et al., 2023), manipulation of needs (Lodziak, 2003; Yılmaz & Tatoğlu, 2024; Senemoğlu, 2017; Rohach & Rohach, 2021). These manipulation concepts can be applied in different areas (e.g., politics, finance), and are particularly common in the field of marketing. While politics and marketing are the areas where manipulation is most prominently used, its effects have also been observed in many disciplines such as media, psychology, finance, and public relations (Begtimur, 2022:10). The primary reason for this is that manipulation is a powerful method aimed at influencing and directing human behavior (Vangeli, 2023:2; Michalak & Stypi□ski, 2023:196). In this context, politicians, managers, mass communication actors, and marketers are among the groups that have most effectively utilized manipulation throughout history (Begtimur, 2022:10).

In marketing, manipulation techniques can be applied in promotional and business activities to facilitate the sale of products and services (Vukasović & Ljubičić, 2022:104). This leads to the possibility of consumers encountering manipulation techniques in their daily lives (Ljubičić & Vukasović, 2023:11). Advertising strategies, pricing policies, shrinkflation[3], consumer purchasing processes, product features, product placement, labeling, packaging designs, fake word-of-mouth (WOM), fake user reviews, campaigns, and consumer experience, when combined with the use of personal data on online platforms, result in the widespread use of manipulation techniques in the marketing field. This can lead to consumers being guided consciously or unconsciously, directly affecting their decision-making mechanisms.

The impact of manipulation in fields such as journalism, photography, and social media is becoming increasingly evident (Atan et al., 2013:2). Social media stands out as an effective tool for manipulating masses, and it is noted that manipulative content can spread rapidly through these platforms (Atan et al., 2013:2). Platforms like social media, e-commerce, and search engines present content based on users' interests, and techniques such as hypernudging and micro-targeting[4] are used in this process (Çaycı, 2021:909). For example, Facebook and other advertising platforms use user data for marketing purposes by allowing advertisers to select specific users and target them with well-crafted messages (Chouaki et al., 2022:1). Applications like filter bubbles ensure that the social media algorithm only allows the individual to consume information that aligns with their interests and ideology (Çaycı, 2021:909). Filter bubbles[5] are cognitive barriers that

3 Shrinkflation: It is a strategy where the size, quantity, or weight of a product is reduced while keeping the price constant or limiting the price increase to a minimum level (Erdoğan & Gürbüz, 2023:1). This strategy is considered a manipulative marketing method because it may lead consumers to unknowingly purchase less product for the same price. Especially when the reduction in product quantity or size is not explicitly stated, consumers may engage in purchasing behavior without noticing this change, creating the impression that companies are manipulating consumer behavior.

4 Micro-targeting aims to deliver engaging and relevant messages to individual users, encouraging them to pay attention to the advertisement or take a desired action (such as making a purchase or sharing the message on their social networks).

5 Filter bubbles (the personalized flow of information tailored to an internet user's preferences and past interactions) can limit how a person views the world and what information they can

emerge as a result of excessive personalization, limiting digital consumers' ability to notice alternative offers, products, or service options (Karaman, 2021:1347-1348). In this regard, journalist and writer Serdar Kuzuloğlu states that *"the addictive nature of social media platforms for users and their continuous use throughout the day does not indicate that the content is consumed unconsciously or of high quality. The main reason for this is the influence of the algorithms operating behind the content.*" According to Kuzuloğlu, algorithms are developed as a result of the collective efforts of psychiatrists, psychologists, behavioral scientists, algorithm experts, and other scientists from various disciplines (gencenderun/instagram.com/19.02.2025).

The role of manipulation in the communication process is also quite prominent, and it is well known that mass media plays a central role in manipulation strategies. Mass media not only targets individuals but also communities, functioning as a tool for mass guidance (Elitaş, 2022:115-116). In the context of mass media, manipulation is manifested through the misguiding and directing of the masses with a one-way flow of news. Information from the news source is restructured during the process from production to consumption and presented in different contexts, gaining a manipulative function (Fırat, 2008:22-23). Especially in digital environments where individuals are constantly online, manipulation strategies through visual and auditory messages are applied systematically (Elitaş, 2022:115-116).

Algorithms play a critical role in various sectors such as healthcare, finance, transportation, education, and agriculture, aiming to increase efficiency, optimize processes, and make more accurate predictions. In this regard, it can be said that algorithms have a significant impact across numerous sectors and have become an indispensable element of daily life (Arıcan Kaygusuz, 2023:534). However, effective management of this process requires the use of data (Witzenberger, 2017:17). Algorithmic analyses based on personal data and user behaviors have the potential to influence individuals' decisions. These strategies are implemented through the use of personal data (Karaman, 2021:1341), and it is known that they

access. When the content on the internet is solely customized for the individual, it may become difficult for them to encounter different perspectives and new information. In other words, a filter bubble refers to the intellectual isolation created when websites selectively present information through algorithms that analyze data such as users' clicking habits, browsing and search history, and location. In this case, users are only exposed to content that aligns with their interests and previous preferences, significantly reducing the likelihood of encountering differing opinions and alternative information (Pariser, 2011 cited in Boyacı Yıldırım & Özgen, 2024:511).

are more likely to produce manipulative outcomes. In practice, when data is processed, attention is drawn to the Personal Data Protection Law.

4. The Effects of Algorithmic Manipulation on Consumer Behavior

Businesses aim to influence consumers' decision-making processes in favor of their products or services by utilizing various stimuli and communication techniques (Yurtsever & Akın, 2022:257). To achieve this, they intentionally implement various strategies to capture consumers' attention and enhance their loyalty. However, at a certain point, these strategies go beyond merely persuading the consumer and start to subtly and covertly direct their behavior, essentially manipulating them (Reuille-Dupont, 2023:17). For instance, the smell of bread in a supermarket evokes positive associations and encourages consumers to purchase, or the use of the color green creates the perception that a product is environmentally friendly, both serving as concrete examples of this phenomenon (Akgün, 2021:271).

The field of marketing has always been an unexplored aspect of the economic system, and each year, marketing techniques and marketing itself evolve in parallel with new technologies. (Vukasović & Ljubičić, 2022:103). With the expansion of marketing, the area of manipulation, which now has many subheadings and subcategories, is also growing. Consumers' right to make free choices is a fundamental source of motivation that shapes their behavior. However, even when consumers are independent of external influences, they may not have full control over the outcomes of their decisions (Wertenbroch et al., 2020:430-431). According to a study, an algorithm created by analyzing data on a consumer's shopping receipt reveals that consumers who buy chips often purchase cola as well. Based on this information, store management may aim to increase sales by placing the chips and cola shelves next to each other to optimize sales strategies (Arıcan Kaygusuz, 2023:534).

Businesses continually focus on consumers' needs and, in order to attract them, may resort to exploiting their thoughts and desires or creating marketing strategies with deceptive guidance (Yurtsever, 2023:52). Marketing strategies aim to shape consumers' perceptions and guide their purchasing decisions, sometimes incorporating elements of conscious manipulation. Specifically, the unconscious direction of consumers toward certain preferences makes the role of manipulation in marketing processes a subject of debate.

It is stated that the information obtained about consumer behavior can be used not only to understand the consumer and shape production processes based on their needs, but also to manipulate the consumer. This information can be used to consciously or unconsciously influence consumers' purchasing decisions in favor of the business (Strang, 2014:248-249). A business can influence the consumer's decision-making process with covert and targeted strategies, often in its own interest. In this case, although the consumer may think they are making decisions freely, the majority of these decisions are actually shaped within the framework pre-determined by the organization (Witte, 2024:3-4). The consumer, unaware of the manipulation, may believe they are making an independent choice, but in reality, these decisions have been directed through manipulative methods (Vukasović & Ljubičić, 2022:103).

The primary goal of manipulations is to prevent consumers from making conscious and rational decisions, encouraging them to purchase a particular product or service through automatic responses or emotional influences. This allows businesses to gain control over consumer behavior. The strategies used in these types of manipulations generally involve emotional, psychological, and behavioral tactics aimed at influencing consumers' decision-making processes without their awareness (Susser et al., 2019:1). Baron (2003) categorizes manipulation into three main categories: deception, coercion, and strategies based on emotions, emotional needs, or character weaknesses (Baron, 2003, cited in Witte, 2024:3-4). Similarly, Michalak and Stypi□ski (2023:203) emphasize in their research that manipulation, particularly based on influencing emotions, has a significant impact on consumer decisions.

One of the new dimensions that manipulation has gained with digitalization is algorithmic manipulation, especially conducted through algorithms (Vangeli, 2023:13). Digital marketers can influence consumer decisions through algorithms and direct these decisions in a way that creates the illusion that consumer autonomy is preserved and they are making their own choices. In this case, while consumers are made to feel that they have more control and freedom, in reality, their behaviors and choices are predetermined and directed by algorithms (Wertenbroch et al., 2020: 430-431). These algorithms used on digital platforms strategically filter and organize the content individuals are exposed to, thereby shaping their preferences and behaviors in a specific direction (Vangeli, 2023:13).

Algorithms provide a significant advantage for businesses in analyzing consumer behavior. By processing big data analytics quickly and efficiently, they determine consumer preferences, habits, and needs, thereby helping businesses develop strategies that better meet customer expectations. Additionally, algorithms optimize business processes, increase efficiency, and accelerate decision-making processes. In this regard, algorithms become a core component of consumer-focused applications and innovative business models (Karaman, 2021:1341). Furthermore, on e-commerce platforms, algorithms offer personalized product recommendations based on users' past purchasing behavior and habits, while on social media platforms, they suggest content based on viewing habits (Arıcan Kaygusuz, 2023:534). Moreover, businesses aim to increase consumer engagement and gain an economic advantage over competitors by pre-designing consumer interactions. These strategies increasingly blur the line between persuasion and manipulation. In the process of directing consumers toward specific decisions and behaviors, algorithmic manipulations are used by analyzing their preferences and habits (Özuz Dağdelen, 2024:35). To reduce the excessive burden of options that consumers face when making choices, businesses use recommendation algorithms and targeting methods. These algorithms can enhance perceived autonomy by making it easier for consumers to find the products and information they prefer. However, at the same time, these systems can expose consumers to more external influences during their decision-making process, which may weaken their real autonomy. This creates a paradox between perceived autonomy and real autonomy (Wertenbroch et al., 2020: 432). Although digitalization is said to make consumer behavior more independent and faster, granting greater autonomy in decision-making processes (Şen, 2024:18), the ability to influence consumers through digital manipulation techniques can violate this autonomy and hinder their decision-making processes with their free will (Susser et al., 2019:8). Thus, while the algorithms underlying digitalization provide consumers with more information, they also have the power to shape their decision-making processes through hidden influences.

The intervention of algorithms can weaken consumers' ability to make independent choices and may turn them into a part of a strategic manipulation aimed at keeping them on the platform for longer periods. This leads to an unconscious impact on the consumer's autonomy[6] (Wertenbroch et al., 2020: 432). For example, false reviews and ratings can create a misleading impression about the quality of a product or service. Comments such as

---

6 Consumer autonomy refers to an individual's ability to remain independent from external pressures, particularly from excessive influence or manipulation by marketers, during the purchasing or decision-making process. In this context, it means that consumers can make their decisions solely based on their own information and will, without external imposition or control (Drumwright, 2016 cited in Bjørlo, 2021:2).

"*Amazing! The product exceeded my expectations, you must buy it!*" may be used to portray a product as being of higher quality than it actually is, even though the reviews are fake. All of these strategies can disrupt consumers' more conscious decision-making processes and manipulate their behaviors. These types of manipulations can have negative effects, especially on consumer autonomy (Susser et al., 2019:1).

Consumers may share small amounts of personal data in order to gain autonomy. For example, when users conduct a Google search to obtain useful information, they share their data in exchange for information. However, these small-scale data-sharing actions can lead to a larger flow of data and manipulation over time. As a result, consumers may unknowingly lose their autonomy. This situation is often likened to the famous "frog in boiling water" story (Wertenbroch et al., 2020: 432). For instance, when a consumer buys a shirt from an e-commerce site, the website's algorithm may suggest similar clothing or complementary products. While this may appear to be a recommendation system based on the consumer's preferences, over time, the system may lead the user towards specific products, potentially causing manipulations that lead to impulsive shopping decisions (Çalapkulu & Buran, 2023:142).

In today's society, many systems that are part of consumers' social lives (such as online shopping, search engines, and navigation apps) operate through algorithms (Striphas, 2015, cited in Witzenberger, 2017: 17). Through social media platforms, individuals can benefit from consumer-oriented positive contributions such as information sharing, participation in public discussions (Vangeli, 2023: 2), access to entertainment, socializing, and freedom of expression. These platforms, while having functions such as raising social awareness, organizing awareness campaigns, and strengthening interpersonal bonds, can also provide a space for the spread of disinformation campaigns and manipulative content (Yılmaz, 2024: 3; Tekke & Lale, 2021: 56). Deepfake technology can be used to manipulate faces with high realism. Nowadays, there are numerous deepfake videos created, particularly targeting celebrities and politicians, circulating on the internet. These videos are often used to damage the reputations of celebrities or to manipulate public opinion, posing a serious threat to social stability (Yu et al., 2021: 607).

Social media algorithms provide businesses with valuable data about consumers, enabling them to gain insights and improve user experience (Saurwein & Spencer-Smith, 2021: 225). While they offer users an environment where they can move freely and select and view the content they desire, they can also have negative effects that raise societal concerns. One of the primary negative impacts is the potential for algorithms to create an infrastructure that encourages harmful behaviors (Saurwein & Spencer-Smith, 2021: 225). Social media applications use various strategies through algorithms to keep users on the platform for longer periods. This can weaken individuals' perception of making free choices and lead them to display behaviors that are unconsciously guided, or in other words, manipulated (Wertenbroch et al., 2020: 432). For example, after viewing a brand's page on Instagram, the consumer may be shown advertisements for similar brands, businesses, and products, which are facilitated by algorithms within the platform (Çalapkulu & Buran, 2023: 142). Facebook uses data and algorithms to determine whether users belong to ethnic minority groups and serves them targeted advertisements specific to those groups (Saurwein & Spencer-Smith, 2021: 227). During the 2016 U.S. Presidential election, the Trump campaign used Facebook ads to specifically target African American voters (Green & Issenberg, 2016: 1). In this context, algorithms, particularly through online advertising, can also lay the groundwork for discriminatory practices. Algorithms are used as an infrastructure to target or exclude certain user groups, which can lead to various harmful effects (Saurwein & Spencer-Smith, 2021: 227).

The widespread adoption of new digital and online sociotechnical systems, such as artificial intelligence-based social media, micro-targeted advertising[7], and personalized search algorithms, has led to significant changes in the ways user interactions, data collection, and behavior influence are conducted. However, because these technologies and techniques have the capacity to target and influence individuals on an unprecedented scale, in a more sophisticated, automated, and pervasive manner, they raise concerns about their manipulation potential and spark various debates (Ienca, 2023: 833). As a person continues to use a social media platform like Instagram, the platform collects more data about the user's online habits. This data is recorded, classified, and analyzed, creating a personalized mental model of the user (Jago, 2022: 159). This model allows for the delivery of personalized content and advertisements based on the user's interests, interaction patterns, and behavior.

---

7 Micro-Targeted Advertising: A technique used by advertisers to deliver personalized and highly targeted messages to specific individuals or groups based on demographic, behavioral, or psychographic characteristics. This technique involves collecting and analyzing large amounts of data from various sources, such as social media platforms, search engines, and third-party data providers, and using this data to create highly customized advertising campaigns (Ienca, 2023: 839).

Through algorithms and personalization techniques, platforms such as YouTube, Netflix, and Instagram recommend similar content as users watch videos they like (Susser et al., 2019:1). Although features like Instagram's Reels, TikTok's Explore, and YouTube's Shorts claim to offer users the opportunity to choose the videos they want, the majority of this content is directed by the platforms' algorithms. While users may think they are making free choices, the algorithms present content based on their interests and previous interactions, thereby guiding their attention to certain videos. This situation creates an illusion of freedom, while users are actually exposed to a content flow determined by the platforms (Wertenbroch et al., 2020:432).

Bjørlo (2021:15) argues that the weakening of consumer autonomy hinders individuals' ability to make decisions freely, and that this has negative effects on consumer welfare and social sustainability. In this context, it is also significant that manipulation conducted through artificial intelligence and related digital technologies is qualitatively no different from manipulation through human-to-human interactions in the physical world, and can violate certain fundamental freedoms or rights concerning the individual's mind and thoughts (Ienca, 2023:833).

Conclusion and Recommendations

Businesses view being strong and effective as a key strategy to increase consumption rates and direct consumers to their own brands. Digital channels play a critical role in providing access to and interaction with consumers, while the data collected from these platforms enable the development of personalized marketing strategies. Technological advancements offer the potential to enhance consumer experiences in conjunction with marketing activities. However, marketing strategies implemented on digital platforms do not always remain within ethical boundaries. Manipulative techniques, which risk directing or misleading consumer behavior, lead to ethical debates.

In digital environments, algorithms are among the key elements that guide consumers and increase consumption behavior. The data collection and processing capabilities of digital platforms make algorithmic manipulation an important tool in marketing strategies. While algorithms shape consumer behavior through targeted product or service presentation, they can also pave the way for unethical practices. The impact of AI-powered algorithms on marketing is increasing, but this impact does not always have a positive outcome and carries the risk of undermining consumer autonomy. Particularly, AI-based manipulation techniques promote unconscious consumption decisions, raising serious ethical concerns.

In the future, as marketing practices based on algorithms become more widespread, this will require stricter and normative regulations regarding ethical use. In this context, regulations play a crucial role in protecting consumer rights and keeping businesses within ethical boundaries. At the same time, it is important for consumers to recognize the algorithmic manipulations they encounter in digital environments and make conscious decisions. Consumer awareness and education should accelerate in parallel with the rise of digital manipulation. This study, which could guide future research, offers several suggestions to the literature:

• Studies should be conducted to examine the effectiveness of educational programs aimed at increasing consumer awareness of algorithmic manipulation. The role of digital literacy in combating manipulation should be addressed in detail.

• Research should focus on examining the impact of algorithmic manipulation on consumer autonomy. Particularly, studies that define ethical boundaries and evaluate whether these boundaries are violated are of significant importance.

• The use of AI-based algorithms in marketing processes, how they shape ethical boundaries, and their long-term effects on consumer autonomy should be investigated.

• Research on the effects of global and local regulations aimed at setting ethical standards in digital marketing practices and limiting algorithmic manipulation should be increased.

• Studies should be conducted to examine the effects of algorithmic manipulation used on social media platforms on consumer behavior.

References

Albers, N., Neerincx, M. A., & Brinkman, W. P. (2022). Addressing People's Current And Future States In A Reinforcement Learning Algorithm For Persuading To Quit Smoking And To Be Physically Active. *Plos One*, 17(12).1-31.

Altuncu, D., Çelebi Şeker, N. N., & Karaoğlu, M. (2013). Mekan Algısında Duyuların Etkisi/Manipülatif Mekanlar. *Sanat Tasarım ve Manipülasyon Sempozyum Bildiri Kitabı İçinde, Sakarya Üniversitesi, Sakarya*, 115-119.

Akgün, A.A. (2021). *Tutundurma Dışındaki Pazarlama Karması Unsurları Bağlamında Pazarlama İletişimi ve Manipülasyon*. (Ed. Osman Çalışkan). Çarpıtılmış Gerçekliğin İnşası Cilt 1 Medya Ve İletişim Mesleklerinde Manipülasyon. Nobel Yayınları. Ankara.

Altun, C. (2018). Okul Öncesi Öğretim Programına Algoritma Ve Kodlama Eğitimi Entegrasyonunun Öğrencilerin Problem Çözme Becerisine Etkisi. *Yayınlanmamış Yüksek Lisans Tezi*. Eğitim bilimleri Enstitüsü. Ankara Üniversitesi

Arıcan Kaygusuz, N. (2023). Nöropazarlama ve Yapay Zekâ İlişkisinin Tüketici Davranışları Üzerindeki Etkisine Yönelik Kavramsal Bir Model Önerisi. *Journal of Academic Social Science Studies*, 16(95).527-547.

Atan, A. Uçan, B. & Renkçi, T. (2013) Çağdaş Sanat Ve Tasarımda Manipülasyon Etkileri. Sakarya Üniversitesi Güzel Sanatlar Fakültesi 1. *Uluslararası Sanat Sempozyumu Sanat, Tasarım ve Manipülasyon Sempozyumu Bildiri Kitabı.*

Bastos, M. (2024). *Social Media Manipulation*. In Brexit, Tweeted. Bristol University Press. 104-114.

Begtimur, M.E. (2022). Oyunun Adı: Manipülasyon. (Ed. Cihad İslam Yılmaz). Psikolojik Harp, Post-Truth ve Stratejik İletişim. *NEU Press*.Konya.

Bjørlo, L., Moen, Ø., & Pasquine, M. (2021). The Role Of Consumer Autonomy In Developing Sustainable AI: A Conceptual Framework. *Sustainability*, *13*(4).

Boldyreva, E. L., Grishina, N. Y., Duisembina, Y., L Boldyreva, E., & Y Grishina, N. (2018). Cambridge Analytica: Ethics And Online Manipulation With Decision-Making Process. European Proceedings of Social and Behavioural Sciences, 51.

Botes, M. (2023). Autonomy And The Social Dilemma Of Online Manipulative Behavior. *AI and Ethics*, 3(1), 315-323.

Boyacı Yıldırım, M., & Özgen, E. (2024). Dijitalleşme Ekseninde İnfodemi Ve Bilgi Düzensizlikleri. *Akademik Hassasiyetler*, *12*(25), 500-529.

Calo, R. (2013). Digital Market Manipulation. Geo. Wash. L. *Rev*., 82, 995.

Chaudhuri, A. B. (2020). *Flowchart And Algorithm Basics: The Art Of Programming*. Mercury Learning and Information. New Delhi.

Chouaki, S., Bouzenia, I., Goga, O., & Roussillon, B. (2022). Exploring the online micro-targeting practices of small, medium, and large businesses. *Proceedings of the ACM on Human-Computer Interaction*, 6(CSCW2), 1-23.

Christiano, T. (2022). Algorithms, Manipulation and Democracy. *Canadian Journal Of Philosophy*, *52*(1), 109-124.

Cormen, T. H., Leiserson, C. E., Rivest, R. L., & Stein, C. (2009). *Introduction To Algorithms,* Third Edition. The MIT Press

Coşkun Keskin, S., Karaloğlu, İ., & Erdoğan, H. (2023). Harezmi Eğitim Modeli'nin Uygulayıcıları Olan Öğretmenlerin Görüşleri Doğrultusunda İncelenmesi. *Ondokuz Mayis University Journal of Education Faculty,* 43(1), 121-140.

Çalapkulu, Ç., & Buran, N. (2023). Dijital Pazarlama Bileşenlerinde Duygusal Zeka Ve Big Datanın Önemi. *İstanbul Ticaret Üniversitesi Girişimcilik Dergisi*. *7*(13). 138-154.

Çaycı, A. E. (2021). Sosyal Medya Platformlarının Kamusal Tartışmalardaki Rolü: Filtre Balonu Ve Yankı Odası. Asead 7. Uluslararası Sosyal Bilimler Sempozyumu Ejser 7th International Symposium On Social Sciences 10-12 nisan/april 2021 kemer – antalya. https://www.researchgate.net/profile/merve-gezen-3/publication/365520187_asead_7_uluslararası_sosyal_bılımler_sempozyumu/links/6377d78854eb5f547ce30206/asead-7-uluslararası-sosyal-bılımler-sempozyumu.pdf#page=922

Elitaş, T. (2022). Dijital Manipülasyon 'Deepfake'teknolojisi Ve Olmayanın İnandırıcılığı. *Hatay Mustafa Kemal Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, *19*(49), 113-128.

Erdoğan, Z. & Gürbüz, E. (2023). Enflasyon Dönemlerinde Pazarlama Karması Uygulamalarını Etkileyen Küçültme Enflasyonu (Shrinkflation) Ve Nitelik Kaybı Enflasyonu (Skimpflation) Stratejileri. *Journal of Politics Economy and Management*, 6(2), 1-20.

Ergül Güvendi, N. (2023). *Manipülasyon Panoraması*. (Ed.Enis Baha Biçer, Orhan ŞANLI). Sosyal, İnsan ve İdari Bilimlerde Güncel Yaklaşımlar. Duvar Yayınları. İzmir.

Eryılmaz, H.(1999). Bir Kitle İletişim Aracı Olarak Haber Fotoğrafı ve Manipülasyon, *Yayınlanmamış Doktora Tezi*, Eskişehir, Anadolu Üniversitesi Sosyal Bilimler Enstitüsü Basım ve Yayımcılık Anabilim Dalı.

Fırat, N. S. (2008). Savaş Fotoğraflarının Kullanımı Bağlamında Propaganda ve Manipülasyon. Marmara Üniversitesi Güzel Sanatlar Enstitüsü, *Yüksek Lisans Tezi*, İstanbul

Finn, E. (2017). *What Algorithms Want: Imagination In The Age Of Computing*. 7 Massachusetts Institute of Technology. Campridge.

Fletcher, G. G. S. (2021). Deterring algorithmic manipulation. *Vand. L. Rev.*, *74*, 259.

Fu, H., & Sun, Y. (2024). Unravelling the algorithm manipulation behavior of social media users: A configurational perspective. In Li, E.Y. et al. (Eds.) Proceedings of The International Conference on Electronic Business, 24. 536-550.

Green, J., & Issenberg, S. (2016, October 26). Why the Trump machine is built to last beyond the election. Bloomberg. https://www.bloomberg.com/news/ articles/2016-10-27/inside-the-trump-bunker-with-12-days-to-go

Greiss, D. (2021). Addressing Digital Market Manipulation In Australian Law. ANU Journal of Law and Technology, 2(2), 23-55.

Ienca, M. (2023). On Artificial İntelligence And Manipulation. Topoi, 42(3), 833-842.

Isinkaye, F. O., Folajimi, Y. O., & Ojokoh, B. A. (2015). Recommendation Systems: Principles, Methods And Evaluation. *Egyptian İnformatics Journal*, 16(3), 261-273.

Jago, E. (2022). Algorithmic Manipulation: How Social Media is Shaping our Theology. *Eleutheria: John W. Rawlings School of Divinity Academic Journal*, *6*(1), 9.

Jiaying, L & Lasi, M.A. (2023). Marketing Manipulatıon: A Literature Review Of Its Antecedents, Mechanisms, Outcomes, And Moderators. International Journal Of Advances Research in Islamic Studies and Education Arise. 3(4). 69-81.

Karaman, Ö. (2021). Yapay Zekâ Destekli Kişiselleştirme Algoritmalarının Tüketici Zihninde Filtre Balonu Yaratma Etkisinin İncelenmesi. Süleyman Demirel Üniversitesi Vizyoner Dergisi, 12(32), 1339-1351.

Karaöz Akın, B., & Gürsoy, Şimşek, U.T. (2018). Adaptif öğrenme sözlüğü temelli duygu analiz algoritması önerisi. *Bilişim Teknolojileri Dergisi*, 11(3), 245-253.

Kayıhan, B., Narin, B., Fırat, D., & Fırat, F. (2021). Algoritmalar, Yapay Zekâ Ve Makine Öğrenimi Ekseninde Gazetecilik Etiği: Uluslararası Akademik Dergilere Yönelik bir inceleme. *TRT Akademi*, *6*(12), 296-327.

Kitchin, R. (2019). Thinking Critically About And Researching Algorithms. In *The social power of algorithms.* Routledge. 14-29.

Li, X., & Li, K. J. (2023). Beating The Algorithm: Consumer Manipulation, Personalized Pricing, And Big Data Management. *Manufacturing & Service Operations Management*, 25(1), 36-49.

Li, W., Bao, L., Chen, J., Grundy, J., Xia, X., & Yang, X. (2024). Market Manipulation Of Cryptocurrencies: Evidence From Social Media And Transaction Data. *ACM Transactions on Internet Technology*, 24(2), 1-26.

Ljubičić, K., & Vukasović, T. (2023). Manipulation In The World Of Marketing. Mednarodno Inovativno Poslovanje. *Journal Of Innovative Business And Management*, 15(1), 1-11.

Lodziak, C. (2003). Kapitalizm ve Kültür, İhtiyaçların Manipülasyonu. (Translator: Berna Kurt), Çitlembik Yayınevi, İstanbul.

Maathuis, C., & Kerkhof, I. (2023). Social Media Manipulation Awareness Through Deep Learning Based Disinformation Generation. *In International Conference on Cyber Warfare and Security.* 18(1). 227-236).

Maathuis, C., & Godschalk, R. (2023). Social Media Manipulation Deep Learning based Disinformation Detection. In International Conference on Cyber Warfare and Security 18 (1). 237-245.

McKee, P. C., Senthilnathan, I., Budnick, C. J., Bind, M. A., Antonios, I., & Sinnott-Armstrong, W. (2024). Fear of Missing Out's (FoMO) Relationship With Moral Judgment And Behavior. *PloS one*, 19(11).

Michalak, J., & Stypiński, M. (2023). Methods of Manipulation Used in Advertising. *Olsztyn Economic Journal*, 18(2), 195-206.

Miyazaki, S. (2012). Algorhythmics: Understanding Micro-Temporality In Computational Cultures. Computational Culture http://computational-culture.net/algorhythmics-understanding-micro-temporality-in-computational-cultures/

Mucundorfeanu, M., Balaban, D. C., & Mauer, M. (2024). Exploring The Effectiveness Of Digital Manipulation Disclosures For Instagram Posts On Source Credibility And Authenticity Of Social Media Influencers. *International Journal of Advertising*, 1-31.

Özuz Dağdelen, E. (2024). *Sosyolojik Bakış Açısıyla Veri Bilimcilerin Gözünden Veri İhlali ve Veri Manipülasyonu Ayrımı*. Sosyolojinin Geleceği ve Geleceğin Sosyolojisi II. Ulusal Kongre Genişletilmiş Özet Bildiri Kitapçığı Taslağı, 31-36.

Önder, D. (8 Şubat 2024). Algoritmalar ve Akış Diyagramı. Medium.com. https://medium.com/@onderrdogukan/algori%CC%87tmalar-ve-aki%C5%9F-di%CC%87yagrami-79229f88183d Access Date: 20.11.2024

Özkök, Ö. (2019). *Sosyal Medyada Sanal Kimlikler; Sosyal Medya Fenomenlerinin Benlik Sunumları Üzerine Bir Araştırma*. Yüksek Lisans Tezi. İstanbul Kültür Üniversitesi, Eğitim Enstitüsü.İstanbul.

Putniņš, T. J. (2012). Market Manipulation: A Survey. *Journal Of Economic Surveys*, 26(5), 952-967.

Reaves, S., Bush Hitchon, J., Park, S. Y., & Woong Yun, G. (2004). If Looks Could Kill: Digital Manipulation Of Fashion Models. *Journal of Mass Media Ethics,* 19(1), 56-71.

Reuille-Dupont, J.C. (2023). The Power of Algorithms and Big Data: A Marketing Perspective on Consumer Manipulation in Business. *Portland State University*. https://pdxscholar.library.pdx.edu/cgi/viewcontent.cgi?article=2540&context=honorstheses

Rickert, T. J. (2024). Ambient Engineering: Hyper-Nudging, Hyper-Relevance, and Rhetorics of Nearness and Farness in a Post-AI Algorithmic World. Rhetoric Society Quarterly, 54(5), 413-430.

Rohach, O. & Rohach, I. (2021). Manipulation and Persuasion in Business Advertising. *Research Trends in Modern Linguistics and Literature*, 4, 47-61.

Saurwein, F., & Spencer-Smith, C. (2021). Automated Trouble: The Role Of Algorithmic Selection İn Harms On Social Media Platforms. *Media and Communication*, *9*(4), 222-233.

Sayılı, A. & Dosay, M. (1991). Hârezmi ile Abdülham id İbn Türk ve Orta Asya'nın Bilim ve Kültür Tarihindeki Yeri. *Erdem Dergisi. 7*(19). 101-214.

Senemoğlu, O. (2017). Tüketim, Tüketim Toplumu Ve Tüketim Kültürü: Karşılaştırmalı Bir Analiz. *İnsan Ve İnsan,* 4(12), 66-86.

Shekhar, H. Seal, S., Kedia, S. & Guha, A. (2018). *Survey on Applications of Machine Learning in the Field of Computer Vision.* (Ed. Jyotsna Kumar Mandar ve Debika Bhattacharya). Emerging Technology in Modelling and Graphics. Springer. 667-678.

Singh, V., Vishvakarma, N. K., & Kumar, V. (2024). Unveiling Digital Manipulation And Persuasion İn E-Commerce: A Systematic Literature Review Of Dark Patterns And Digital Nudging. *Journal Of Internet Commerce*, 23(2), 144-171.

Strang, W. A., Lusch, R. F. & Laczniak, G. R. (2014). *Consumer Manipulation: Are Marke ters Building A Monster?. Venkatakrishna.* (Ed. V. Bellur). Proceedings of the 1980 Academy of Marketing Science. (AMS) Annual Conference içinde USA: Springer. 248-253.

Susser, D., Roessler, B., & Nissenbaum, H. (2019). Technology, Autonomy, And Manipulation. *Internet Policy Review*, 8(2).1-22.

Susser, D., Roessler, B., & Nissenbaum, H. (2019a). Online Manipulation: Hidden İnfluences İn A Digital World. *Geo. L. Tech. Rev.,* 4(1).

Şen, B. (2024). Pandemi Döneminde Dijitalleşmenin Tüketici Davranışlarına ve E-Ticaret Stratejilerine Etkisi. *Tokat Gaziosmanpaşa Üniversitesi Turhal Uygulamalı Bilimler Fakültesi Dergisi*, 2(2), 11-20.

Tan, P. L., Tjiptono, F., & Tan, S. Z. (2024). Fear More Or Fear No More: Examining The Emotional And Behavioral Consequences Of FOMO And JOMO. *Asia Pacific Journal of Marketing and Logistics.* 1-22.

Tekke, A., & Lale, A. (2021). Sosyal Medyada Etik, Bilgi Manipülasyonu ve Siber Güvenlik. Akademik İncelemeler Dergisi, 16(2), 44-62.

Yılmaz, Y., & Tatoğlu, M. F. (2024). Televizyon Programlarında İzleyici İhtiyaçlarının Manipülasyonu: MasterChef Türkiye Analizi. Kocaeli Üniversitesi *İletişim Fakültesi Araştırma Dergisi*, (24), 61-79.

Yu, P., Xia, Z., Fei, J., & Lu, Y. (2021). A Survey On Deepfake Video Detection. *Iet Biometrics*, 10(6), 607-624.

Yurtsever, A.E. (2023). Manipülatif Pazarlamanın Z Kuşağının Davranışsal Niyetleri Ve Tüketim Alışkanlıklarına Etkileri. (Ed. Murat Akın). İSAD Publising House. https://dx.doi.org/10.5281/zenodo.8250397

Yurtsever, A. E., & Murat, A. (2022). Cep Telefonu Şirketlerinin Kullandıkları Manipülatif Satış Tekniklerinin Z Kuşağındaki Tüketicilerin Davanışsal Niyetleri Ve Tüketim Alışkanlıkları Üzerindeki Etkisi. Social Science Development Journal (Ssd Journal), 7(33), 257-283.

Quinelato, P. D. (2024). Consumer Manipulation Through Behavioral Advertising: Regulatory Proposal By The Data Services Act. Brazilian Journal of Law, *Technology and Innovation,* 2(1), 1-24.

Wertenbroch, K., Schrift, R. Y., Alba, J. W., Barasch, A., Bhattacharjee, A., Giesler, M., & Zwebner, Y. (2020). Autonomy İn Consumer Choice. *Marketing letters*, *31*, 429-439.

Wikipedia.org. Algortima. https://tr.wikipedia.org/wiki/Algoritma Access Date: 03.01.2025

Witte, J. (2024). Consumer Manipulation–A Definition, Classification And Future Research Agenda. Journal Of Information, Communication and Ethics in Society. doi/10.1108/JICES-09-2023-0119

Witzenberger, K.(2017). What Users Do to Algorithms. *Media and Communication Studies, Lund University*

https://www.kom.lu.se/fileadmin/user_upload/kom/Filer/PDF/MKV/FEA-rapporter/Web_version_RR_2017_1_2_.pdf#page=19

Vangeli, M. (2023). The Philosophy of Algorithmic Manipulation: Unveiling the Influence of Social Media Algorithms. Uppsala University, Disciplinary Domain of Humanities and Social Sciences, Faculty of Arts, Department of Philosophy. https://www.diva-portal.org/smash/get/diva2:1770486/FULLTEXT01.pdf Erişim Tarihi:04.01.2024

Vukasović, T., & Ljubičić, K. (2022). *Marketing Manipulation in the 21st Century*. In 5 th International Scientific Conference ITEMA 2021–Conference Proceedings.

Chapter 3

Privacy and Artificial Intelligence

Engin Yavuz[1]

Abstract

The areas of use of artificial intelligence are constantly increasing. It has started to play a major role especially for brands to increase sales by influencing consumers. In an increasingly competitive environment, it is vital to reach more consumers and increase sales rates. Consumers prefer the option they find closer to themselves among brands due to easy access to products and services and the abundance of options. Therefore, the demand for personalized products and services is increasing day by day. Brands also need more information to offer personalized products to consumers. It is very difficult to access consumers' personal data and make meaningful inferences from them, especially with large amounts of data. Artificial intelligence makes the work of brands much easier at this point. Consumer data, most of which is collected on the internet, can be analyzed with artificial intelligence and meaningful information can be obtained. Recently, however, there have been some concerns about the collection and use of consumer data. Personal data may be improperly shared with third parties and may lead to legal problems. Artificial intelligence developers should ensure that personal data is collected and used in line with principles such as transparency, fairness, accountability, privacy and security. The establishment of an effective control system and the sanctions to be taken against violations should be clearly stated. Providing the necessary support from governments and ensuring global cooperation can contribute to the reduction of personal data breaches. In this section, within the scope of privacy and artificial intelligence, the definition of artificial intelligence, the privacy of consumers and artificial intelligence, the views of the European Data Protection Board on the use of personal data, the views of the OECD on the use of personal data, the Council of Europe's ethical principles on artificial intelligence are examined under the headings.

1 Dr. Amasya Üniversitesi, engin84yavuz@gmail.com, https://orcid.org/0000-0002-9644-4946

https://doi.org/10.58830/ozgur.pub710.c3020

Privacy and Artificial Intelligence

1. Introduction

In recent years, the number of consumer concerns about ethical issues in online shopping has continued to grow. Privacy and security are considered by consumers and researchers to be the most important ethical violations (Román and Cuestas 2008). The possibility of artificial intelligence violating privacy is increasing day by day. Although privacy is considered a fundamental right, it should be taken into account that artificial intelligence may lead to violations of privacy protection (Akyol and Özkan, 2023: 122).

Digital technology environments are being used more and more in daily life. However, it has become possible to talk about the privacy of private life with the data collected, archived, analyzed and interpreted as a result of artificial intelligence consisting of platforms, software, codes and algorithms (Wilson, 2016). With these developments, it can be considered that artificial intelligence prepares the ground for revealing personal freedoms and privacy (Gül, 2018: 20).

Technological developments bring about changes in daily life. Artificial intelligence, which is one of them, has risks affecting human rights as well as areas where it is beneficial. Especially in areas such as trade, communication and cybercrimes, malicious use is also possible. This situation prompts politicians, states and artificial intelligence developers to develop new strategies (Dost, 2023: 1275).

Having data, which is the basis of artificial intelligence, also brings power. In today's increasingly competitive environment, it is critical for both private sector organizations and governments to gain power. Therefore, governments and private organizations may want to access personal data as soon as possible and use it for their own interests. By capturing the personal data of the target audience, they can use it to market products and services in accordance with the wishes of consumers and to increase their sales. When this data is not used properly, it may mean a violation of consumers' privacy (Varkonyi, 2018: 3).

Artificial intelligence technologies can easily obtain sensitive personal data by processing data that is not considered sensitive. In other words, artificial intelligence technologies can cause violation of private life by converting non-sensitive data into sensitive data. Personal data can be extracted through social media platforms such as Facebook, Instagram, etc. and consumers' virtual identities can be captured. With this data, consumers' interests, tendencies and expectations can be learned and used in commercial activities (Abudureyimu and Oğurlu, 2021: 771).

In this section, within the scope of privacy and artificial intelligence, the definition of artificial intelligence, the privacy of consumers and artificial intelligence, the views of the European Data Protection Board on the use of personal data, the views of the OECD on the use of personal data, the Council of Europe's ethical principles on artificial intelligence are examined under the headings.

2. Artificial Intelligence

There is not yet an agreed definition of artificial intelligence. However, according to the definition by the European Commission of Human Rights, artificial intelligence is "used as an umbrella term to refer to a set of sciences, theories and techniques dedicated to improving the ability of machines to do things that require intelligence. An artificial intelligence system is a machine-based system that produces recommendations, predictions or decisions for a given set of goals (European Commission of Human Rights, 2019)".

The concept of artificial intelligence should be characterized as an algorithm-supported artificial machine that can learn in a complex and variable field, make decisions, influence those around it, and transfer the information and decisions it obtains to users, that is, an entity with the ability to think (Gezici, 2023: 112).

If we define artificial intelligence briefly, it is a technology-based system that analyzes simultaneous product and service simulations using data obtained from both digital and physical channels and makes personalized recommendations to solve consumers' complex problems and answer their questions, enabling them to decide between options (Xu et al., 2020).

3. Consumer Privacy and Artificial Intelligence

Artificial intelligence uses algorithms to calculate the probabilities that are likely to occur using the data they obtain and tries to gain useful information as a result. For example, artificial intelligence algorithms are used extensively in areas such as tourism, logistics, retail and e-commerce to monitor competitors' prices and determine price policies accordingly, to determine consumer preferences and to analyze the data obtained (Öz, 2020: 40).

Artificial intelligence also makes extensive use of consumers' personalized data in shopping and entertainment. Amazon's purchase recommendations, Netflix's efforts to direct the audience, prioritizing consumers in terms of content and making consumer-specific recommendations. At this point, consumers evaluate what to buy or not to buy, which product or service will be beneficial for them through artificial intelligence rather than individual thoughts (Eltimur, 2022: 578).

Artificial intelligence in marketing is frequently used in areas such as analyzing consumer behavior, consumer experience, providing personalized products and services, and managing consumer relationships quickly and effectively before, during and after sales. In consumer research, abilities such as understanding, speech and cognitive abilities are performed by the algorithms of artificial intelligence (Huang & Rust, 2022: 210).

With the increasing use of social media, people share their daily lives and experiences on these platforms. These shares are increasing day by day. Large amounts of data can reach many people simultaneously with the internet. Consumers' personal information, what they like and dislike, and their thoughts are very important for marketing practitioners. It becomes difficult to process large amounts of data into meaningful information. Artificial intelligence is one of the most effective ways to turn difficult into easy (Binbir, 2021: 315).

However, in addition to these benefits, artificial intelligence may use personal data improperly to increase consumer satisfaction. The information obtained through digital traces while browsing the internet and the advertisements developed through this information are just one of the many violations in the field of artificial intelligence. The large amount of data collected from consumers also raises issues related to their private lives. These problems are not only related to data management. In addition, directing consumer preferences and encouraging them to buy the products and services they want is one of the steps that restrict consumers' freedom. For example, with the consumer data obtained, artificial intelligence algorithms can identify certain consumers and manage their perceptions (Gonçalves et al., 2023: 315).

Aleksandr Kogan, a researcher at the University of Cambridge, collected users' personal data on Facebook without their consent and transmitted it to Cambridge Analytica. The personal data obtained targeted consumers through advertising. After the personal data breach was revealed, the company was shut down. In order to prevent this vulnerability, Facebook blocked Cambridge Analytica's access and launched an investigation into applications that similarly had access to personal data. It also restricted third-party developers from accessing personal profiles (The Guardian, 2018).

4. Various Organizations' Views on Privacy and Artificial Intelligence

Although obtaining personal data provides great advantages to brands, the use and sharing of data without taking the necessary privacy and security measures can harm consumers as well as brands (Danışman, 2023: 161). In this section, the views of the European Data Protection Board, the OECD and the Council of Europe on the use of personal data are given.

4.1. Opinions of the European Data Protection Board on the Use of Personal Data

On December 18, 2024, the European Data Protection Board (EDPB) issued an opinion on the use of personal data in the use of artificial intelligence. According to this opinion (European Data Protection Board, 2025):

1) When and how AI models will be considered anonymous:

Whether an AI model is anonymous or not depends on the decision of countries' data protection authorities and may need to be assessed on a case-by-case basis. For an AI model to be considered anonymous;

a) Direct or indirect identification of the persons whose data are used in the creation of the artificial intelligence model.

b) It is necessary to prevent personal data from being obtained from the artificial intelligence model through querying.

2) Procedures required to develop or use artificial intelligence models:

A representative should be provided by AI developers so that users can communicate when necessary and necessary measures should be taken to increase cyber security. These measures can be beneficial for users and provide legal protection, but only if the processing of personal data is truly necessary and personal rights are respected.

3) Unlawful development of artificial intelligence:

Unless artificial intelligence models are duly anonymized, the use of personal data may be unlawful.

4.2. OECD's Views on the Use of Personal Data

According to the report published by the OECD, there is a need for global coordination to solve the problems related to the data used by artificial intelligence. In this report, six issues are highlighted in order to harmonize the developments in the field of artificial intelligence with privacy principles (Maxwell, et. al., 2024). These are (Maxwell, et. al., 2024):

1) Privacy in the use of artificial intelligence

Complaints about privacy violations in the use of artificial intelligence are increasing and the measures to be taken to address this issue are important. Particular attention needs to be paid to privacy in the conceptualization, development and deployment phases of artificial intelligence actions. It is important to comply with privacy rules from the early stages of AI development and design, and to make proactive efforts to close gaps in implementation. Building bridges between societies, making privacy a permanent policy in AI development and supporting privacy-oriented innovation are among the critical issues (Shrestha and Joshi, 2025; Mooradian et. al, 2025; Maxwell, et. al., 2024).

2) Cooperation between communities

Terminological and conceptual misunderstandings in AI privacy and policies can lead to ambiguities. Therefore, it is important to build sustainable interactions between AI communities. In this way, terminological and conceptual harmonization between AI communities on privacy-related issues can be achieved and contribute to the development of AI (Welsh et al., 2024; Maxwell, et. al., 2024).

3) Justice

It is very important for AI models to process personal data fairly and reach conclusions in terms of privacy principles of AI. Principles such as limitation of data collection, purposefulness, openness and quality of data collected are critical to ensure fairness (Verma et al., 2024; Maxwell, et. al., 2024).

4) Transparency and accountability

Obtaining consent when processing individuals' data and informing them about how it is used is one of the most important issues in artificial intelligence development. As transparency increases, so does trust, making it easier for users to make informed decisions. Practical solutions such as model cards can be produced to ensure that the information provided by AI is understandable and meaningful (Cheong, 2024; Maxwell, et. al., 2024).

5) Accountability

It is also important to be able to integrate privacy and risk management principles into AI applications at the design stage and, as a result, to be accountable and comply with the laws of countries. Deep privacy detection programs to detect privacy can also help prevent breaches (Moch, 2024; Maxwell, et. al., 2024).

6) Global cooperation

Global synchronization, guidance and collaboration are needed to help AI mitigate privacy concerns. While there have been improvements in global collaboration, increased efforts can help prevent privacy violations. In addition, Privacy Enhancing Technologies (PETs) can bridge this gap to a large extent to help with data management and privacy safeguards (Al-Billeh et al., 2024; Maxwell, et. al., 2024).

4.3. Council of Europe Ethical Principles on Artificial Intelligence

According to the guidelines published by the Council of Europe in 2019, a trustworthy AI must meet the following 7 basic requirements (European Comission, 2019):

1) Oversight of human activities:

AI should empower individuals and support them in decision-making. In addition, it is important that artificial intelligence systems are controllable.

2) Technical infrastructure and security:

Artificial intelligence systems need to be strong and stable in terms of infrastructure. It is also critical to prevent security breaches.

3) Privacy and data management:

Artificial intelligence systems should provide legitimate access to data and pay due attention to its quality and confidentiality.

4) Transparency:

Artificial intelligence applications should follow a transparent management policy. Users should be informed about whether they are interacting or not. In addition, users should be informed about the capabilities and limitations of artificial intelligence applications.

5) Fairness:

AI models should treat users equally and fairly. It should be ensured that all users can access AI models without any discrimination.

6) Social contribution:

Artificial intelligence models should benefit all of humanity, with future generations in mind. They should also be respectful of the environment and take care to provide social benefits.

7) Responsibility:

Mechanisms are needed for artificial intelligence applications to fulfill their responsibilities and to be accountable within the framework of these responsibilities. it is also important that the design processes of the data can be audited.

Sonuç

Artificial intelligence has been used extensively in marketing in recent years. Due to increased competition, businesses want to increase their market share or at least maintain their status. Consumers have many options when making purchasing decisions. Considering that consumers want to choose the brands that provide the most suitable personalized products/services with the increase in their alternatives, businesses may have to benefit from artificial intelligence in order to fulfill the wishes of consumers. Artificial intelligence can collect consumer data, analyze it, and then make it available to marketing practitioners. Collecting, analyzing and transforming consumer data into useful information is a complex and difficult process that can only be accomplished through AI-enabled applications with current technology (Neves and Pereira, 2025).

Artificial intelligence applications should pay attention to legal regulations when obtaining consumer data and take the necessary measures for the use of personal data. When collecting personal data, it should be transparently explained to consumers what data is collected and for what purpose. Businesses should not ignore the principle of transparency in order to gain the trust of consumers. In addition to affecting consumer trust, breach of personal data may put businesses in a difficult situation in front of the law. Therefore, businesses that follow an artificial intelligence-supported marketing strategy should pay close attention to the security of personal data and the privacy of private life (Kır, 2024: 71).

Artificial intelligence applications used by businesses must fulfill ethical and legal responsibilities when collecting personal data from consumers. Inappropriate collection of personal data and sharing it with third parties without permission may lead to personal data breach and may result in legal sanctions. Ensuring global cooperation and the necessary sanctions by states by taking measures against personal data breach can prevent the improper collection of personal data breach. In addition, artificial intelligence developers should have the ability to communicate with consumers when necessary and build infrastructure systems to prevent the improper collection of personal data (Muvva, 2025).

Kaynakça

Abudureyimu, Y. ve Oğurlu, Y. (2021). Yapay zekâ uygulamalarının kişisel verilerin korumasına dair doğurabileceği sorunlar ve çözüm önerileri. *İstanbul Ticaret Üniversitesi Sosyal Bilimler Dergisi*, 20(41), 765-782, doi:10.46928/iticusbe.863505

Al-Billeh, T., Hmaidan, R., Al-Hammouri, A., & Makhmari, M. (2024). The risks of using artificial ıntelligence on privacy and human rights: unifying global standards. *Jurnal Media Hukum*, *31*(2), 333–350. https://doi.org/10.18196/jmh.v31i2.23480

Akyol, İ.T. ve Özkan, N.A.Ş. (2023). Yapay zeka uygulamalarinin yerel hizmet sunumuna etkisi, *Tokat Gaziosmanpaşa Üniversitesi Sosyal Bilimler Araştırmaları Dergisi*, 120-134.

Avrupa İnsan Hakları Komisyonu. (2019). Unboxing artificial intelligence: 10 steps to protect human rights, Erişim Adresi: chrome extension://efaidnbmnnnibpcajpcglclefindmkaj/https://rm.coe.int/unboxing-artificial intelligence-10-steps-to-protect-human-rights-reco/1680946e64 Erişim Tarihi: 16.02.2025

Binbir, S. (2021). Pazarlama çalışmalarında yapay zeka kullanımı üzerine betimleyici bir çalışma, *Yeni Medya Elektronik Dergisi*, 5(3), 314-328.

Cheong, B. C. (2024). Transparency and accountability in AI systems: safeguarding wellbeing in the age of algorithmic decision-making. *Frontiers in Human Dynamics*, *6*. https://doi.org/10.3389/fhumd.2024.1421273

Danışman, G.T. (2023). Artificial Intelligence in Terms of Digital Marketing: A Conceptual Examination. In: Fettahlıoğlu, H. S. & Bilginer Ozsaatcı, F. G. (eds.), *Digital Transformation of Marketing: Marketing 5.0*. Özgür Publications. DOI: https://doi.org/10.58830/ozgur.pub254.c1340

Dost, S. (2023). Yapay zekâ ve uluslararası hukukun geleceği' 13(2) *Süleyman Demirel Üniversitesi Hukuk Fakültesi Dergisi* 1271, 1313.

Eltimur, D.E. (2022). İnsan haklarının korunması bağlamında yapay zekâ uygulamaları, *Akdeniz Üniversitesi Hukuk Fakültesi Dergisi*, 12(2), 559-594.

European Comission. (2019). Ethics guidelines for trustworthy AI, Erişim Adresi: https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai, Erişim Tarihi: 18.02.2025

European Data Protection Board. (2025). Erişim Adresi: https://www.edpb.europa.eu/news/news/2024/edpb-opinion-ai-models-gdpr-principles-support-responsible-ai_en, Erişim Tarihi: 20.02.2025

Gezici, H.S. (2023). Kamu yönetiminde yapay zekâ: Avrupa Birliği, *Uluslararası Akademik Birikim Dergisi,* 6(2), 111-128.

Gonçalves, A. R., Pinto, D. C., Rita, P. ve Pires, T. (2023). Artificial Intelligence and its ethical implications for marketing, *Emerging Science Journal*, 7(2), 313-327. doi: 10.28991/ESJ-2023-07-02-01

Gül, H. (2018), Dijitalleşmenin kamu yönetimi ve politikaları ile bu alanlardaki araştırmalara etkileri, *Yasama Dergisi*, 36, 5-26.

Huang, M.H. ve Rust, R.T. (2022). A framework for collaborative artificial intelligence in marketing. *Journal of Retailing*, 98(2), 209–223.

Kır, B. (2024). AI Pazarlama: Yeni Bir Paradigma, (Ed. M. Nur Erdem, Cansu Maya), Marka İletişimi Tüm Boyutlarıyla Marka ve Tüketici Etkileşimi (içinde), Palet Yayınları: Konya

Öz, G.A. (2020). Corona (Covid 19) gölgesinde geleceğin hukuku ve dijital ekonomi çağinda rekabet hukuku, *Ankara Üniversitesi Hukuk Fakültesi Dergisi*, 69 (1), 33-56.

Shrestha, A. K., & Joshi, S. (2025). Toward Ethical AI: A Qualitative Analysis of Stakeholder Perspectives. https://doi.org/10.48550/arxiv.2501.13320

Maxwell, W., Girot, C. ve Perset, K. (2024). Six crucial policy considerations for AI, data governance, and privacy: Insights from the OECD, Erişim Adresi: https://oecd.ai/en/wonk/six-policy-considerations-ai-data-governance-and-privacy, Erişim Tarihi: 19.02.2025

Moch, E. (2024). Liability Issues in the Context of Artificial Intelligence: Legal Challenges and Solutions for AI-Supported Decisions. *East African Journal of Law and Ethics*, *7*(1), 214–234. https://doi.org/10.37284/eajle.7.1.2518

Mooradian, N., Franks, P. C., & Srivastav, A. (2025). The impact of artificial intelligence on data privacy: a risk management perspective. *Records Management Journal*. https://doi.org/10.1108/rmj-06-2024-0013

Muvva, S. (2025). Ethical AI and responsible data engineering: A framework for bias mitigation and privacy preservation in large-scale data pipelines. *Indian Scientific Journal of Research In Engineering and Management*, 09(01), 1–8. https://doi.org/10.55041/ijsrem10633

Neves, J. ve Pereira, M. C. (2025). A marketing perspective on the roles of AI and ML in shaping contemporary programmatic advertising. *International Journal of Digital Marketing, Management, and Innovation* (IJDMMI), 1(1), 1-14. https://doi.org/10.4018/IJDMMI.368043

Román, S., Cuestas, P., 2008. The perceptions of consumers regarding online retailers' ethics and their relationship with consumers' general Internet expertise and word of mouth: a preliminary analysis. *Journal of Business Ethics,* 83, 641–656.

The Guardian. (2018). Cambridge Analytica closing after Facebook data harvesting scandal, Erişim Adresi: https://www.theguardian.com/

uk-news/2018/may/02/cambridge-analytica-closing-down-after-facebook-row-reports-say, Erişim Tarihi: 15.02.2025.

Xu, Y., Shieh, C., Van Esch, P. ve Ling, I. (2020). AI customer service: Task complexity, problem-solving ability, and usage intention, *Australasian Marketing Journal*, 28(4), 189-199.DOI:10.1016/j.ausmj.2020.03.005

Varkonyi, G.G. (2018). Robots with AI: Privacy considerations in the era of robotics. Law 4.0 1-12, Györ: Széchenyi István University, Erişim Adresi: https://www.academia.edu/36293091/Robots_with_AI_Privacy_Considerations_in_the_Era_of_Robotics Erişim Tarihi: 17.02.2025.

Verma, S., Paliwal, N., Yadav, K., & Vashist, P. C. (2024). *Ethical Considerations of Bias and Fairness in AI Models*, 2nd International Conference on Disruptive Technologies (ICDT), 818–823. https://doi.org/10.1109/icdt61202.2024.10489577

Welsh, C., Román García, S., Barnett, G. C., & Jena, R. (2024). Democratising artificial intelligence in healthcare: community-driven approaches for ethical solutions. *Future Healthcare Journal*, *11*(3), 100165. https://doi.org/10.1016/j.fhj.2024.100165

Willson, M. (2016). Algorithms (and the) Everyday, Information, Communication & Society.

Chapter 4

Consumer Distrust: Non-Transparent AI Decision-Making Processes

Murat Başal[1]

Abstract

Today, artificial intelligence (AI) has emerged as a pivotal technology that influences decision-making processes across various domains, including digital marketing and customer relations. However, the lack of transparency in AI systems, coupled with their failure to provide consumers with adequate clarity regarding their decision-making processes, significantly contributes to consumer distrust. This uncertainty, often referred to as the "black box consumers to adopt a skeptical and cautious attitude toward brands and the services they offer.

Non-transparent AI decision-making processes can lead to consumer distrust. Factors such as perceived injustice, data privacy concerns, and ethical uncertainties are believed to undermine consumer confidence, ultimately affecting purchasing decisions. Consumers increasingly demand transparency, auditability, and adherence to ethical principles to trust automated decision-making systems. Therefore, it is essential for brands to embrace the principle of transparency, enhance the comprehensibility of AI-based systems, and elevate their ethical responsibilities to restore consumer trust.

The growing prevalence of AI-based decision-making processes presents numerous opportunities for consumers; however, it also raises significant trust issues. Non-transparent AI systems impede consumers' ability to comprehend how decisions are made, resulting in diminished levels of trust.

Consumers often struggle to understand how artificial intelligence (AI) operates and the criteria it employs to make decisions. AI systems can yield unfair or discriminatory outcomes due to biases present in the datasets utilized. Furthermore, uncertainties surrounding the use of personal data erode consumer trust in AI-based systems.

1 Assist Prof., Istanbul Gelisim University, mbasal@gelisim.edu.tr, ORCID: 0009-0004-5666-9560

https://doi.org/10.58830/ozgur.pub710.c3021

AI can sometimes mislead consumers by relying on inaccurate or incomplete information. To address these challenges, it is essential to enhance transparency policies, develop explainable AI models, and implement regulations that safeguard consumer rights. By taking these measures, we can bolster consumer trust in AI-based systems.

1. Entry

Today, the consumption habits of individuals have started to be changed with algorithms and analytical solutions developed with artificial intelligence Technologies (Acar & Tanyıdızı, 2022). Thanks to these algorithms, it is possible to direct people to products that they do not actually need as if they were essential needs and to change their consumption habits. In addition, it is clear that artificial intelligence will play a very important role in gaining customers who have a positive experience, are more satisfied, and whose loyalty and satisfaction are ensured as a result of functions such as personalization, real-time sentiment analysis, decision-making and harmonization (Bayuk & Demir, 2019; Biçkin et al., 2021).

In recent years, consumers have been doing most of their shopping online. Artificial intelligence is used in these shopping sites and social media platforms, and this arouses interest and curiosity in consumers. In response to this interest, virtual assistants and chatbots supported by artificial intelligence technologies are changing people's decisions to search, evaluate and purchase information with personalized recommendations. However, the way people consume goods and services is guided by artificial intelligence (Akbaba & Gündoğdu, 2021; Aylak et al., 2021).

2. Conceptual Framework

2.1. Consumer Insecurity

Consumer confidence appears as an important element in the success of the relational marketing approach. Enterprises need to constantly obtain information about consumer expectations, which are constantly changing and differentiating. Improving relations with consumers also brings positive economic results in the long term. Trust is subjective as it is based on the beliefs and behaviors of consumers. Consumers feel loyalty to brands that give them confidence. In order to build trust, both the supplier and the buyer need to fulfill their promises. A stable brand personality and the nature of the products or services will increase the brand's credibility by reducing the emotional risk that buyers experience when making purchases (Binbir, 2021; Borgesius, 2017).

The main purpose of marketing is to create a deep bond between the consumer and the brand, and the most important element of this bond is trust. Trust is considered the most critical feature a brand can have, while at the same time it forms the cornerstone of the relationship and is seen as one of the most sought-after qualities in a relationship (Sucu, 2019; Şahinci, 2021). The existence of trust increases consumers' loyalty and commitment to the brand, which supports the sustainable success of the brand in the long term. Consumer skepticism is often used to refer to consumers' distrust of marketers' intentions, specific advertising claims, and public relations efforts. This concept reflects consumers' developing a negative attitude towards marketing communications and their skepticism of marketers' actions (Şalvarlı & Kayışkan, 2022).

This process leads to the development of trust and satisfaction. Especially when the belief that the brand supports consumers increases and expectations are met, a bond forms between the buyer and the supplier decently (Zengin, 2020). Trust is a value that should be protected for businesses. In the event of any crisis that businesses will experience, trust in the brand will be shaken, as well as other brand components will be affected by this situation (Erdem, 2022; Zengin, 2021).

Trust in the business is the basis of the relationship between the supplier and the buyer. Consumers tend to buy products or services from a trusted business. As a result of the research conducted, buying products from brands that give confidence increases the consumer's motivation. Thus, in the process of purchasing products or services, trust appears as a risk-reducing factor (Binbir, 2021; Borgesius, 2017).

Consumer trust refers to the belief that consumers have in a business, brand or seller and the feelings of security and trust in their interactions with these parties. This concept affects the trust that consumers have in the other party during product or service purchases and how this trust is formed. Consumer trust plays a critical role in businesses achieving positive results such as customer loyalty, repeat purchase behaviors and positive word-of-mouth marketing. Consumer trust refers to the level of trust and belief that consumers have in a brand. Brand trust is positively correlated with brand loyalty and is defined as "the average consumer's willingness to trust the ability of the brand to fulfill its stated function". With the trust that a brand has gained from consumers, consumers are generally less inclined to question and tend to interact with the brand without any doubt (Şalvarlı & Kayışkan, 2022).

Therefore, consumers who trust a brand are more likely to be exposed to greenwashing practices because consumers feel less risk and have less doubt. Abuse of consumer trust can occur by presenting misleading information or hiding information that has environmental impacts. When fraud is detected, consumer trust and positive perception of the consumer may be damaged (Sucu, 2019; Şahinci, 2021).

While gains are made as long as trust continues, losses may occur when trust ends. The fact that trust ends in a relationship damages reputation is a threatening situation. Therefore, in a trust relationship based on calculation, the fear of loss is a greater determinant than the benefit that the gain will bring (Binbir, 2021; Borgesius, 2017).

In a trust relationship based on information, the cooperation of the other person is not necessary for the formation of trust. Predictability is sufficient for the formation of trust. Trust based on information; It is formed over time with the development of communication and relationships.

In trust based on identification, it is the case that the parties understand and appreciate each other's desires well. In line with this common understanding, people work for each other's benefit. The parties can replace each other and are sure that their own interests are protected without the need for control (Uma et al. 2020; Topoyan, 2020).

Artificial intelligence (AI)-based systems guide decision-making processes in many areas of daily life. However, the transparency of these systems causes a significant sense of insecurity in his personality. The storage of data on how artificial intelligence stores its decisions, what data is distributed, and how fair the data is, makes it difficult for consumers to secure these systems (Erdem, 2022; Zengin, 2021).

Developing a new product or improving an existing product offers a competitive advantage to businesses and brands in terms of identifying potential customers and satisfying existing customers. On the other hand, the products developed or improved provide performance increases with the use of technology (Zengin, 2020). By predicting the physical and emotional behaviors of individuals, the process of developing new products provides less time, less effort and higher success by using artificial intelligence algorithms. In addition, artificial intelligence applications enable higher quality, more relevant and more personalized product and service delivery to the user by providing customization and personalization and hyper-personalization on products and services (Zengin, 2021).

Thus, it provides an advantage in terms of providing customer satisfaction. The value that the consumer is willing to pay to own or use any good, service or idea is defined as the price. The price determined according to the direct relationship between cost and profit directly affects the stability of the enterprises, the value and quality of the services, products and ideas offered Decently.

2.1.1. Factors Affecting Consumer Confidence

Trust has always been an important element in influencing consumer behavior. In an uncertain environment such as internet-based e-commerce transactions, the issue of trust becomes even more important. Consumers may differ in terms of their tendency to trust and their willingness to trust (Ton & Su, 2018). The tendency or willingness to trust is influenced by consumers' awareness of internet fraud and their past experiences with both the internet and other risky situations. From a marketing point of view, trust is important in terms of customer relationship management. For this reason, over the past decade, the issue of trust has become an important topic in consumer behavior research (Toufailiy et al. 2013; Tsiotsou, 2016).

While trust depends on face-to-face personal relationships in traditional commerce, transaction processes are the most important factor in building trust in e-commerce businesses. The key to success in e-commerce businesses is to create an environment where businesses can be confident in all transactions for consumers and to establish reliable transaction processes (Ton & Su, 2018). To gain consumer trust, e-commerce businesses must convince potential consumers that the information obtained through commercial transactions will remain confidential. E-commerce businesses use various security mechanisms to increase their perceived credibility. These include privacy policy notices, third-party certification programs, the quality of website design, consumer testimonials or reviews, recommendations from reference groups, and money-back guarantees. The trust that a consumer attributes to a product or brand image is based on their experience with that brand (Briley & Aaker, 2006).

Therefore, trust as an experience characteristic will be influenced by the consumer's assessment of their direct and indirect contact with the product/brand (advertising, word-of-mouth, brand reputation) (Bianchi & Mathews, 2016). Consumer trust in e-commerce is highly dependent on feedback mechanisms such as consumer perceptions and consumer evaluations. Online consumer ratings are typically offered by previous consumers of the product or service who rate their experience on a scale (ranging from "one star - bad experience" to "five stars - excellent experience") (Bravo et al. 2007).

Gaining consumers' trust has long been considered one of the important issues by marketers. This situation requires businesses to take various risks (such as developing new products, providing support services and entering new markets) in order to increase their market and financial performance (Chen, 2018). However, recent studies have clearly shown that consumer trust is based in part on ethical considerations related to the business's marketing activities. This is because, compared to other business functions, marketing is more exposed to external environmental forces and therefore faces some of the greatest ethical challenges (Darley et al. 2010; Davis, 2017).

In shopping, trust refers to the feelings of one party to the reliability and honesty of the other party. Trust reduces the uncertainty that exists in the present. Therefore, trust is important in influencing consumers' fears of deception and uncertainty in trading (Ginosar & Ariel, 2017; Gregory et al. 2017).

In addition to a person's propensity towards trust and other characteristics, general economic, demographic and geographical factors also influence the tendency to make online payments (Hallikainen & Laukkanen, 2018). Today, while millions of consumers are shopping online, it is an important topic of discussion how much the number of consumers who will shop online will increase when full trust is provided in the security system (Ha & Stoel, 2012; Hagberg et al. 2016).

Trust is sensitive and subjective because it is based on consumers' beliefs rather than facts. To build trust, suppliers need to keep their promises (Hanna et al. 2019). A consistent brand personality will reduce the emotional risk that buyers experience when they buy a brand and increase credibility in the nature of the goods or services features (Falk & Hagsten, 2015; Fang et al. 2014).

Building relationships of trust is a challenge that may require e-commerce businesses to go beyond nonprofit thinking to set themselves apart from their competitors (Hasan, 2010; Henseler et al. 2015).

Talent describes the consumer's belief that the relationship partner e-commerce site has the necessary capabilities to perform the job efficiently and effectively (Chen, 2018). This can also be broadly defined as a set of skills and traits in a particular field. Aptitude is also called competence and involves the belief that someone else has the ability to perform what is expected. This information reduces uncertainty in e-commerce. Talent is the feature that expresses that consumer needs can be met by the e-commerce business (Darley et al. 2010; Davis, 2017).

Benevolence means the goodwill of the business to meet the needs of the consumer and at the same time to prevent harm to the consumer. Philanthropy is the ability of a business to put consumer interests above its own, demonstrating a genuine concern for the well-being of consumers (Ginosar & Ariel, 2017; Gregory et al. 2017).

Benevolence also includes the intention to act benevolently towards the consumer when a new circumstance arises in which the business has not committed. In this sense, consumers should be convinced that the business is working to do good things for the consumer beyond the understanding of profitability (Falk & Hagsten, 2015; Fang et al. 2014).

Honesty, on the other hand, refers to the degree to which businesses fulfill the promises made to consumers. The dishonesty of e-commerce operators and the lack of privacy and/or security of the internet environment have negative consequences in gaining consumers (Bianchi & Mathews, 2016). Integrity in e-commerce reflects the consumer belief that the business will deliver products and services to consumers without any problems, keep private and financial information confidential, and keep its promises on sensitive issues such as the like (Bravo et al. 2007; Briley & Aaker, 2006).

The rapid growth in e-commerce depends on many factors such as consumers' trust in e-commerce sites, products and services (Gregory, et al. 2017). Many studies emphasize that trust is important for consumers to be enthusiastic about e-commerce. For example, trust has an impact on whether consumers are willing to connect with a website and provide information. In addition, it has been shown that a high level of trust is linked to a high degree of purchase intention (Fang, et al. 2014; Ginosar & Ariel, 2017).

Although internet retailers incur high protection costs to protect their systems, they can be exposed to security attacks by cyber fraudsters. These incidents not only lead to loss of revenue for the retail store, but also cause negative perceptions of transaction security against consumers. For this reason, it is very important to understand the large investments made to increase trust and security and to measure them in order to take better action (Falk & Hagsten, 2015).

2.2. Elements of Insecurity Caused by Non-Transparent AI Decision-Making Processes

Although social changes and technology have affected consumer behavior in every period, various developments such as the pandemic, especially in the last five years, have caused radical changes in consumers' daily lifestyles and purchasing behaviors (Zengin, 2021). In 2019, individuals have started to show changes such as being ageless and natural, hanging out alone, being a more conscious consumer, digital togetherness, feeling expert, not deliberately chasing the very popular (Joy of Missing Out-JoMO), being self-sufficient, contributing to the world, and wanting speed (Erdem, 2022). Especially in the years following the pandemic, it is seen that the use of robots and artificial intelligence has increased in many areas, as consumers have become much more sensitive individuals in every subject (Zengin, 2020).

In this period, consumers have started to use smart watches, smart homes, smart vacuum cleaners, and even their willingness to pay more for these products has increased (Topoyan, 2020). Considering all these; It can be predicted that the market share of products equipped with artificial intelligence technologies will increase. Therefore, with the increasing and widespread use of artificial intelligence-supported technologies in human life, significant changes have started to occur in decision-making processes and behaviors as consumers (Uma et al. 2020).

In recent years, consumers have been doing most of their shopping online. Artificial intelligence is used in these shopping sites and social media platforms, and this arouses interest and curiosity in consumers (Topoyan, 2020). In response to this interest, virtual assistants and chatbots supported by artificial intelligence technologies are changing people's decisions to search, evaluate and purchase information with personalized recommendations. However, the way people consume goods and services is guided by artificial intelligence (Uma et al. 2020).

Natural Language Processing (NLP), which enables understanding and analyzing human language in understanding and communicating with customers, machine learning that enables informed decision-making by data analysis and automatic adaptation, chatbots and virtual assistants to provide fast, efficient customer support and service, and artificial intelligence technologies such as predictive analytics and sentiment analysis to provide fast, efficient customer support and service (Zengin, 2021). Their feelings and attitudes are much better understood. Artificial intelligence, which supports consumers in finding the right product, is also a resource for influencing consumers. With the spread of this resource, which transforms different areas of industry, people will not need to use their own minds much, that is, there will be no cost of intelligence (Erdem, 2022; Zengin, 2020).

The aim of contemporary marketing activities is to satisfy the wishes and needs of the consumer. It is especially important to know the wants and needs of the consumer and how they can be satisfied. For this, it is necessary to examine and know the factors that affect satisfaction or dissatisfaction (Dmitrieska et al. 2018). A consistent understanding of consumer behavior is vital to the long-term success of marketing strategies. Businesses attract the attention of consumers by making use of a number of algorithms developed from people's previous preferences, tastes and discourses. Individuals who surf the internet or social networks by showing them products that they will like are made to feel as if they definitely need these products. Because artificial intelligence allows businesses to effectively match information about the products and services they offer with the information they need from potential consumers (Doko, 2021; Elgun & Karabıyık, 2022).

Although artificial intelligence applications, which are mostly used for support purposes, play a key role in coping with the uncertainty of the decision-making process, it is not currently possible to use them as decision-makers on their own, since people's personal experience and thought patterns guide decision-making with superior intuition (Choi & Lim, 2020). Past experience, insight and holistic vision are human capital and are human-specific qualities. These qualities are important for strategic problems that can be solved with a holistic approach. It is difficult for artificial intelligence to imitate and replicate human-specific qualities that guide intuitive decision-making. It is a matter of debate that one day, instead of human-AI collaboration, artificial intelligence will be able to replace humans in the decision-making process (Coşkun & Gülleroğlu, 2021).

3. Result

The Decisional process is of great importance for managers who have to choose among the alternatives in every issue that arises. Artificial intelligence applications, the use of which has increased significantly recently, allow the most efficient and efficient use of limited resources by saving time and cost in the processes in which they are used. In the coming years, with the sufficient development of artificial intelligence technologies by consumers, it is observed that artificial intelligence applications will become more involved in the decision-making processes of companies and company managers.

Today, artificial intelligence technology is developing and spreading rapidly in the innovative world. Artificial intelligence technology, which has created significant changes in many industries and sectors, has started to be very effective in consumers' behavior, purchasing habits and decisions. Artificial intelligence applications enable consumers who are faced with a wide variety and number of products with various features to reduce the costs of searching for information, save time and easily decide on the most appropriate option. Consumers can provide many benefits in online product selection with artificial intelligence technologies such as virtual and augmented reality, customer service experiences with smart assistants and robots, reaching appropriate and fast solutions in determining and meeting their needs, providing personalized products, experiences, pricing, marketing messages, campaigns and coupons. Thus, the purchasing decisions of consumers who gain convenience, comfort and low cost advantages in their experiences are positively affected.

The effective use of tools such as unmanned devices, internet of things (IoT), customer relationship management, smart robots in marketing with artificial intelligence technologies that create great changes in customers' profiles is very important for businesses. As a matter of fact, thanks to artificial intelligence, the next steps of customers can be predicted. Thanks to artificial intelligence algorithms, businesses are provided with great convenience in understanding and meeting the demands and expectations of consumers and the changes in these expectations. Therefore, with personalized automation and relevant content, consumers' expectations are met and their loyalty to the business is strengthened. In addition, businesses that develop their marketing strategies by using the existing data of their customers reduce their workload by performing even the simplest tasks with artificial intelligence technology, and new ideas and new content are developed. In this direction, businesses can accurately and easily identify the needs of consumers and create marketing efforts accordingly. In addition, businesses need to carefully evaluate the benefits of artificial intelligence and consider it as an important opportunity for consumer satisfaction and loyalty.

Resources

Acar, H. M. & İmik Tanyıldızı, N. (2022). Reklamda yapay zekâ kullanımı: Ziraat Bankası #senhepgülümse reklam filminde deepfake uygulamasının görsel anlatıya etkisi. Kastamonu İletişim Araştırmaları Dergisi (KİAD), (8), 78-99.

Akbaba, A. İ. & Gündoğdu, Ç. (2021). Bankacılık hizmetlerinde yapay zekâ kullanımı. Journal of Academic Value Studies, 7(3), 298-315.

Aylak, B. L., Oral, O. & Yazıcı, K. (2021). Yapay zekâ ve makineleştirme tekniklerinin lojistik sektöründe kullanımı. El-Cezeri, 8(1), 74-93.

Bayuk, M. N. & Demir, B. N. (2019). Endüstri 4.0 kapsamında yapay zekâ ve pazarlamanın geleceği. Sciences, 5(19), 781-799.

Bianchi, C., & Mathews, S. (2016). Internet marketing and export market growth in Chile. Journal of Business Research, 69(2), 426-434.

Biçkin, P. G., Çiçek, M. & Uncular, M. H. (2021). Teknolojinin pazarlamadaki yeri ve yeni eğilimler: Pegasus Hava Yolları örneği. Gümüşhane Üniversitesi İletişim Fakültesi Elektronik Dergisi, 9(1), 225-254.

Binbir, S. (2021). Pazarlama çalışmalarında yapay zeka kullanımı üzerine betimleyici bir çalışma. Yeni Medya Elektronik Dergisi, 5(3), 314-328.

Borgesius, F. Z. & Poort, J. (2017). Online price discrimination and EU data privacy law. Journal of Consumer Policy, 40(3), 347-366.

Bravo Gil, R., Fraj Andrés, E., & Martinez Salinas, E. (2007). Family as a source of consumer-based brand equity. Journal of Product & Brand Management, 16(3), 188-199.

Briley, D. A., & Aaker, J. L. (2006). Bridging the culture chasm: Ensuring that consumers are healthy, wealthy, and wise. Journal of Public Policy & Marketing, 25(1), 53- 66.

Chen, M. (2018). Improving website structure through reducing information overload. Decision Support Systems, 110, 84-94.

Choi, J. A. & Lim, K. (2020). Identifying machine learning techniques for classification of target advertising. ICT Express, 6(3), 175-180.

Coşkun, F. & Gülleroğlu, H. D. (2021). Yapay zekânın tarih içindeki gelişimi ve eğitimde kullanılması. Ankara University Journal of Faculty of Educational Sciences (JFES), 1-20.

Darley, W. K., Blankson, C., & Luethge, D. J. (2010). Toward an integrated framework for online consumer behavior and decision making process: A review. Psychology & Marketing, 27(2), 94-116.

Davis, R. (2017). A comparison of online and offline gender and goal directed shopping online. Journal of Retailing and Consumer Services, 38, 118–125.

Dimitrieska, S., Stankovska, A. & Efremova, T. (2018). Artificial intelligence and marketing. Entrepreneurship, 6(2), 298-304.

Doko, E. (2021). Makineler aşık olabilir mi?. M. K. Yılmaz, N. Ö. İyigün (Ed.), Yapay Zeka: Güncel Yaklaşımlar ve Uygulamala içinde (345-368). İstanbul: Beta Kitap.

Elgun, M. N. & Karabıyık, H. Ç. (2022). Tutundurmanın bileşenlerinin sınıflandırılması üzerine bir teorik tartışma ve bir tanım önerisi. Econder International Academic Journal, 6(1), 74-85.

Erdem, B. (2022). Yapay zekanın pazarlamaya etkisi, D. Terzioğlu ve S. S. Korkmaz, (Ed.). Sosyal Bilimlerde Disiplinlerarası Akademik Çalışmalar içinde (87-99). İstanbul: Eğitim Yayınevi.

Falk, M., & Hagsten, E. (2015). E-commerce trends and impacts across Europe. International Journal of Production Economics, 170, 357-369.

Fang, Y., Qureshi, I., Sun, H., McCole, P., Ramsey, E., & Lim, K. H. (2014). Trust, satisfaction, and online repurchase intention: The moderating role of perceived effectiveness of e-commerce institutional mechanisms. MIS Quarterly, 38(2). 407-428.

Ginosar, A., & Ariel, Y. (2017). An analytical framework for online privacy research: What is missing?. Information & Management, 54(7), 948-957.

Gregory, G. D., Ngo, L. V., & Karavdic, M. (2017). Developing e-commerce marketing capabilities and efficiencies for enhanced performance in business-to-business export ventures. Industrial Marketing Management. 78, 146-157.

Ha, S., & Stoel, L. (2012). Online apparel retailing: roles of e-shopping quality and experiential e-shopping motives. Journal of Service Management, 23(2), 197- 215.

Hagberg, J., Sundstrom, M., & Egels-Zandén, N. (2016). The digitalization of retailing: an exploratory framework. International Journal of Retail & Distribution Management, 44(7), 694-712.

Hallikainen, H., & Laukkanen, T. (2018). National culture and consumer trust in ecommerce. International Journal of Information Management, 38(1), 97-106.

Hanna, R. C., Lemon, K. N., & Smith, G. E. (2019). Is transparency a good thing? How online price transparency and variability can benefit firms and influence consumer decision making. Business Horizons, 62(2), 227-236.

Hasan, B. (2010). Exploring gender differences in online shopping attitude. Computers in Human Behavior, 26(4), 597-601.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115-135.

Sucu, İ. (2019). Dijital evrenin yeni dünyası olarak yapay zeka ve Her filmi üzerine bir çalışma. Yeni Medya Elektronik Dergisi, 4(1), 40-52.

Şahin, E. & Kaya, F. (2019). Pazarlamada Yeni Dönem Endüstri 4.0, Yapay Zeka ve Akıllı Asistanlar. İstanbul: Çizgi Kitapevi.

Şahinci, D. (2021). Yapay zeka ve reklamcılığın geleceği, (Yayımlanmamış Doktora tezi). İstanbul Üniversitesi Sosyal Bilimler Enstitüsü Radyo Televizyon ve Sinema Anabilim Dalı, İstanbul.

Şalvarlı, M. S. & Kayışkan, D. (2022). Pazarlama alanında yapay zekanın gelişen rolüne genel bir bakış. İzmir Yönetim Dergisi, 2(2), 106-115.

Tong, X., & Su, J. (2018). Exploring young consumers' trust and purchase intention of organic cotton apparel. Journal of Consumer Marketing, 35(5), 522-532.

Topoyan, M. (2022). Endüstri 4.0 ve tedarik zinciri yönetimi, M. Marangoz ve H. H. Özkoç, (Ed.). Endüstri 4.0 ve İşletme Yönetimi içinde (249-276). İstanbul: Beta Basım Yayım.

Toufaily, E., Ricard, L., & Perrien, J. (2013). Customer loyalty to a commercial website: Descriptive meta-analysis of the empirical literature and proposal of an integrative model. Journal of Business Research, 66(9), 1436-1447.

Tsiotsou, R. H. (2016). The social aspects of consumption as predictors of consumer loyalty: Online vs offline services. Journal of Service Management, 27(2), 91- 116.

Uma Devi, N. & Paul V, Maria Tresita.(2020). Artificial intelligence: Pertinence in supply chain and logistics management. Xi'an Jianzhu Keji Daxue Xuebao/Journal of Xi'an University of Architecture & Technology, 12, 701-709.

Zengin, F. (2020). Akıllı makine çağı sinemasına giriş: sinema sanatında yapay zekâ teknolojilerinin kullanımı. İletişim Çalışmaları Dergisi, 6(2), 151-177.

Zengin, F. (2021). Yapay zekâ ve kişiselleştirilmiş seyir kültürü: Netflix örneği üzerinden sanat eserinin hiper kişiselleştirilmesi. TRT Akademi, 6(13), 700-727

Chapter 5

Algorithmic Biases and Injustice: Ethical and Practical Dimensions of Artificial Intelligence in Digital Marketing

Dr. Bahadır Avşar[1]

Abstract

Digital marketing is undergoing a profound transformation with the rise of artificial intelligence (AI) algorithms. These technologies process large datasets to enable personalized campaigns and automation, while simultaneously introducing ethical and practical challenges. This article praises AI's potential in marketing while examining the adverse effects of algorithmic biases, such as discrimination, loss of consumer trust, and risks to corporate reputation. A literature-based analysis reveals that biases stem from distortions in training data, shortcomings in design choices, and socio-cultural contexts. This leads to the exclusion or mis-targeting of specific groups in segmentation and targeting processes, creating unfairness in marketing strategies and acting as a catalyst for deepening societal inequalities. The study proposes solutions, including technical approaches (e.g., fair data processing techniques), ethical frameworks (e.g., transparency and accountability), and regulatory measures (e.g., international standards), offering a holistic framework for the responsible use of AI.

Introduction

Marketing, which is essentially the art and science of understanding consumer demands and developing strategic responses to these demands, has been redefined in the modern era with the impact of digital transformation. The collection and analysis of online data streams have radically changed the discipline. At the same time, AI algorithms have taken the capacity to individualise and mechanise marketing practices to an extraordinary level by processing large data pools - such as demographics, social media trails and purchase histories (Gupta, 2024). However, this technological leap has been

1 TRT, Araştırmacı, OrcidID: 0000-0002-6805-537X

https://doi.org/10.58830/ozgur.pub710.c3022

marred by algorithmic biases based on sensitive attributes such as ethnicity, gender and age, which threaten not only marketing effectiveness but also principles of social justice (Pappadà & Pauli, 2022). This chapter aims to deconstruct the dual nature of AI in digital marketing - its productive potential and ethical vulnerabilities.

In segmentation and targeting processes, AI-induced biases lead to the systematic exclusion or disproportionate targeting of specific social clusters, which fuels consumer discontent and erodes institutional legitimacy (Bigman et al., 2023). Racial biases documented in some social media platforms' ad-targeting algorithms have triggered legal sanctions and public outcry as a concrete manifestation of this problem (McIlwain, 2023). In this context, the study focuses on three main questions: (1) How do algorithmic biases affect the functioning of digital marketing strategies? (2) In what ways do these biases put consumer trust and corporate reputation at risk? (3) What conceptual and practical solutions can be put forward for AI's ethical and responsible implementation? Based on a systematic review of literature published between 2015 and 2024 in Web of Science and Scopus databases, this research rigorously investigates the origins, effects, and ways to mitigate biases.

The proliferation of AI in digital marketing has increased operational efficiency and made systemic flaws and societal consequences sharply visible. Biases in educational data, inadequacies in design decisions, and algorithms shaped by socio-cultural contexts risk perpetuating discriminatory practices; for example, personalised pricing models can reinforce inequalities by disadvantaging low-income consumers (Rathnow, Zeller, & Lederer, 2024). Such practices call into question basic marketing principles such as fair competition and consumer welfare; at the same time, they jeopardise the long-term sustainability of businesses by eroding consumer trust - the cornerstone of brand loyalty (Akter et al., 2022). By scrutinising the tension between the technical capabilities of AI and its ethical limits, this study aims to reveal how this technology operates as both a source of innovation and a tool of injustice.

1. Transformation of Digital Marketing with AI

In the early stages of marketing, mass communication tools such as print media, radio, and television aimed to appeal to large audiences with standardised messages. This was the inevitable result of an approach that ignored individual differences. However, the proliferation of the Internet in the 1990s heralded the birth of digital marketing; measurable and interactive tools such as email campaigns and search engine optimisation (SEO/SEM) reshaped the basic paradigms of this discipline (Babadoğan, 2024). The rise of data analytics in the 2000s dramatically increased the capacity of businesses to monitor and interpret online consumer behaviour. With the explosion of social media and the growth of e-commerce, the volume of data has reached a threshold described as 'big data' (Pasupuleti, 2024). This transformation has transformed marketing from a pure communication activity into a data-driven strategic discipline.

Advanced technologies such as artificial intelligence (AI), machine learning, natural language processing and predictive analytics have redrawn the boundaries of digital marketing. Amazon's recommendation engines have significantly increased conversion rates by providing precise recommendations based on individual consumer preferences. At the same time, Netflix is a concrete example of this transformation by strengthening audience loyalty through dynamic content distribution (Barat & Gulati, 2024). Predictive analytics can predict market trends with an accuracy of 95% (Liu, 2024), taking the capacity of businesses to forecast demand and optimise resources to an extraordinary level (Wang, 2024). However, this technological leap has also brought ethical issues such as data privacy violations, algorithmic biases and lack of transparency in decision-making processes (Elkhatibi & Benabdelouhed, 2024). While extolling the transformative potential of AI, the literature emphasises the urgency of addressing these risks systematically (Dwivedi, 2024).

The integration of AI into digital marketing has not only increased operational efficiency but also radically changed the capacity to individualise consumer experiences. Machine learning algorithms have formed the basis of hyper-personalised strategies by analysing a broad and sophisticated spectrum ranging from social media interactions to previous purchase data (Elkhatibi & Benabdelouhed, 2024). For example, generative AI tools enable marketers to deepen their strategic focus by automating content creation, SEO optimisation, and social media management, making companies more agile and responsive to market demands (Hera, 2024; Mandić, Marković, & Mulović Trgovac, 2024). However, in this process, the phenomenon known as 'filter bubbles' - the exposure of consumers to a limited range of content or products - risks overshadowing the dynamic nature of marketing by suppressing originality and innovation (Babadoğan, 2024). This dilemma makes it clear that the strategic advantages of AI need to be balanced with ethical costs.

Moreover, the role of AI in marketing strategies is not limited to the individual consumer but affects a broader market ecosystem. Predictive analytics and dynamic pricing models have the potential to increase customer satisfaction while maximising ROI through real-time adjustments (Dwivedi, 2024). However, these practices may alienate consumers if personalised pricing is perceived as unfair (Rathnow et al., 2024); for example, algorithms that offer higher prices for low-income groups are controversial from an ethical and competitive perspective. The literature suggests that such practices may distort market competition and reduce the visibility of small-scale businesses, which calls into question the potential of AI to encourage monopolistic tendencies (Csurgai-Horváth, 2024). In this context, the transformative impact of AI in digital marketing is not only a technological issue but also a process of economic and social restructuring.

This technology's lack of ethical and regulatory framework overshadows the innovations that AI offers to digital marketing. Challenges such as data privacy, algorithmic bias, and transparency present the necessity to preserve consumer trust and maintain responsible marketing practices, necessitating businesses to commit more robustly to ethical practices (Tang, 2024). On the other hand, innovative technologies integrated with AI, such as hyper-personalisation, augmented reality (AR) and the Internet of Things (IoT), have the potential to shape the future of marketing (Pasupuleti, 2024).

2. Algorithmic Biases: Sources and Effects

While the AI transformation of digital marketing has brought unprecedented precision and scale to consumer-centric strategies, it has also introduced serious ethical and operational risks, such as algorithmic bias. Algorithmic bias occurs when AI models systematically produce erroneous outputs that favour or disadvantage certain groups, often due to the reflection of inequalities in data (e.g., biases related to race, gender, or socioeconomic status) in algorithms, subjective choices in design processes, or the embedded effects of social norms (Moussawi, Deng, and Joshi 2024; Bigman et al., 2023). In digital marketing, these biases shape processes ranging from targeted advertising to personalised content recommendations, increasing the risk of discrimination, undermining consumer trust, and jeopardising the long-term brand value of businesses (Chen, 2024). Therefore, understanding the origins and dynamics of algorithmic biases is not only a technical issue but also a strategic imperative at the intersection of marketing science and ethical responsibility.

The effects of algorithmic biases on digital marketing are felt across a broad spectrum, from individual consumer experiences to societal structures. When consumers perceive unfair or discriminatory outputs from biased algorithms (e.g., ad targeting that systematically excludes certain demographic groups), their trust in and willingness to engage with digital platforms may decrease, leading to erosion of brand loyalty and reputational damage to businesses (Chen, 2024; Shin, 2024). From a broader perspective, these biases can reproduce social inequalities, limiting access to services and information for marginalised communities, thus creating a cycle that deepens the digital divide. In economic terms, biased algorithms have the potential to affect market dynamics profoundly. Algorithmic bias can distort competition by favouring certain groups, lead to inefficient market outcomes and suppress innovation by providing unfair advantages, thus undermining overall market efficiency (Huang et al., 2024; Basshuysen, 2022). Armed with big data and artificial intelligence, companies can use these biases to their advantage to disadvantage competitors, which may increase market consolidation. At the same time, algorithms that exploit consumers' cognitive biases and information asymmetries may trigger suboptimal purchasing decisions, leading to unnecessary or overpriced products, eroding consumer welfare and deepening economic inequalities (Bar-Gill et al., 2023).

In this context, addressing algorithmic biases is a prerequisite for AI's ethical and practical use in digital marketing. The potential for efficiency and innovation offered by AI systems can only be realised through adherence to the principles of fairness, transparency and accountability at all stages, from these systems' design to implementation (Samala & Rawas, 2024). Otherwise, the risk of prejudices reinforcing existing social structures overshadows the promised benefits of technology.

2.1. Sources of Prejudice

Algorithmic biases in digital marketing have a sophisticated multi-layered web of origins that are not limited to the bias of data sets; they derive from the design paradigms of algorithms (Akter et al., 2022), the socio-cultural contexts in which they are implemented (Singh, 2023), and the strategic prioritisation or revenue-driven models of businesses (Csurgai-Horváth, 2024). For example, an algorithm designed to optimise cost-effectiveness may inadvertently produce discriminatory outputs by inadvertently targeting demographic groups that are less cost-effective to target; such systems may reinforce gender inequalities by systematically making women less visible, as Lambrecht and Tucker (2016) show in their gendered ad targeting in STEM fields. Similarly, social media platforms can marginalise minority perspectives by highlighting content that aligns with dominant cultural norms, suggesting that algorithmic processes are technical and function as a mirror reflecting socio-economic power dynamics (Singh, 2023). Moreover, the business models of digital platforms to maximise user engagement or profit can lead to the stratification of biases by creating an unfair distribution across content types and demographics (Csurgai-Horváth, 2024).

Design Bias: Design bias emerges as a structural flaw arising from the construction processes of algorithms and can systematically favour specific results over others through the basic assumptions of the model, data selection and method preferences (Akter et al., 2022). Such biases are embedded in the technical architecture of algorithms and often derive from the conscious or unconscious decisions of the developers. For example, an algorithm prioritising cost-effectiveness may favour demographic characteristics requiring fewer resources to target. This bias is not only limited to individual outputs; it can also shape the long-term orientation of marketing strategies, systematically restricting the visibility and reach of certain groups. Design bias is thus a crossroads that illustrates the tension between the technical optimisation goals of algorithmic systems and ethical implications.

Contextual Bias: Contextual bias emerges as a reflection of the socio-cultural environment in which algorithms are implemented and is shaped by the infiltration of cultural norms, social dynamics and historical biases into algorithmic decision-making processes (Akter et al., 2022). Such biases show that rather than being neutral tools, algorithms have a symbiotic relationship with the social structures in which they operate. For example, social media platforms may favour content that aligns with dominant cultural tendencies, overshadowing minority voices or alternative perspectives. Singh's (2023) analysis strikingly illustrates how these dynamics accelerate the marginalisation of minority communities in the digital space. This suggests that algorithms internalise the data and the context in which the data is collected and interpreted, proving that bias is not just a technical problem but an extension of social power relations. Thus, Contextual bias necessitates reassessing marketing strategies regarding cultural sensitivity and inclusiveness.

Implementation Bias: Implementation bias is shaped by strategic preferences arising from the way algorithms are used in practice and the business models of digital platforms; these biases are often driven by commercial goals such as profit maximisation or user engagement (Csurgai-Horváth, 2024). In this process, the prioritisation mechanisms of algorithms may favour users with specific demographics or behavioural patterns, creating an unfair distribution of content access and visibility. This type of bias illustrates the conflict between the economic logic of digital marketing and its ethical responsibilities, as profit-driven optimisation can often have consequences that ignore social diversity and equality (Csurgai-Horváth, 2024). Implementation bias, therefore, raises questions about how algorithmic systems are designed, how they are deployed, and what purposes they serve.

2.2. Effects on Marketing Strategies

Algorithmic bias is emerging as a factor that profoundly affects key marketing strategies, transforming how businesses interact with consumers while potentially opening the door to unfair or discriminatory practices. These biases arise from distortions in data sets, structural flaws in the design of algorithmic models and the way they are applied in different contexts, with serious consequences for customer equity and marketing effectiveness.

Firstly, customer segmentation is one of the areas where the most apparent effects of algorithmic bias are observed. Biased data or models can lead to the overrepresentation of certain demographic groups or the systematic omission of others.

Secondly, personalisation and targeting processes can be significantly distorted by the influence of biased algorithms. Chen (2024) shows that bias disrupts personalisation efforts by producing recommendations that do not align with customer preferences or needs. For example, a machine learning model prioritising certain features over others may inadvertently exclude some customer segments or serve irrelevant content.

Third, pricing and promotion strategies are the areas where algorithmic bias's ethical and practical implications are most strikingly evident. Biased algorithms can lead to discriminatory pricing practices towards specific customer segments; for example, biased datasets may offer some groups unfair pricing advantages while disadvantaging others. Similarly, biases in the distribution of promotions can undermine overall marketing effectiveness by preventing promotional efforts from reaching the entire customer base equally. This not only undermines consumer confidence but can also expose businesses to legal and ethical scrutiny.

2.3. Segmentation and Prejudices

In marketing segmentation, algorithms have emerged as indispensable tools that provide businesses with targeted strategies, personalised experiences and optimised resource allocation by segmenting customer bases based on shared characteristics, preferences and behaviours. However, in this process, algorithmic biases emerge as an important factor that threatens segmentation models' accuracy, effectiveness and fairness. They are fed by multiple sources ranging from data collection methods, consumer behaviour assumptions and the algorithmic design.

Algorithms play a fundamental role in marketing segmentation; methods such as K-means, DBSCAN and agglomerative hierarchical clustering provide valuable outputs to businesses by revealing hidden patterns in large datasets. K-means stands out for its simplicity and efficiency; for example, when integrated with RFM analysis, it has been shown to segment consumers based on behavioural patterns with 95% accuracy (Sarkar et al., 2024). DBSCAN performs better in irregular data distributions and noisy environments (Boyko & Protsik, 2024), while agglomerative hierarchical clustering offers global and local perspectives on complex data types (Panda et al., 2024). These algorithms increase customer satisfaction by enabling personalised marketing strategies (Potluri et al., 2024), maximise return on investment by optimising resource allocation (Reddy et al., 2024), and strengthen strategic decision-making processes by revealing hidden trends (Potluri et al., 2024). However, these benefits are overshadowed by the bias-prone nature of the algorithms.

Biases in segmentation processes originate from multiple sources and call into question the reliability of the models. Inaccuracies in self-reported data, such as reporting inconsistencies in postcode-based geodemographic segmentation, can be influenced by demographic factors and produce skewed results (Gladden et al., 2015). Behavioural biases can bias segmentation models by deriving from irrational consumer preferences and decision-making processes (Guhl et al., 2020). Methodological and theoretical shortcomings exacerbate biases due to segmentation frameworks failing to address consumer behaviour holistically (Ji, 2003). Furthermore, choosing loss functions - for example, Cross Entropy or Dice losses - can lead to biased segmentation outputs (B. Liu et al., 2024). Social influence and position biases complicate segmentation, especially in freemium markets, by basing consumer preferences on social dynamics rather than product attributes (Berbeglia, Berbeglia, & Hentenryck, 2021), while economic factors shape segmentation strategies through conditions such as demand and supply elasticity (Martin & Zwart, 1987).

The impact of biases on segmentation is a technical issue and an ethical responsibility. Algorithms can perpetuate discrimination by inheriting social biases found in educational data; for example, AI-driven targeting can reinforce biases associated with protected characteristics such as race or socioeconomic status, and this has been demonstrated by fairness measures such as Disparate Impact (DI) (Soni, 2024). In fields such as healthcare, biased data can lead to inaccurate predictions (Goankar, Cook, & Macyszyn, 2020), while personalised ads can violate ethical standards by providing discriminatory recommendations to low-income groups (Parasrampuria & Williams, 2023). This brings with it the risk that segmentation models may produce misleading and unfair results, jeopardising customer equity and brand reputation.

3. Effects on Consumer Trust and Corporate Reputation

The widespread use of algorithms in marketing strategies has profound and multifaceted impacts on consumer trust and corporate reputation. These effects are mainly due to algorithms' biased outputs, lack of transparency and potential to lead to unethical practices. Academic literature reveals that algorithmic decision-making processes directly shape consumers' perceptions of brands and that these perceptions play a decisive role in the construction or destruction of trust (Susarla, Purnell, & Scott, 2024). In particular, cases where biased algorithms create perceptions of unfairness erode consumer trust in businesses while simultaneously exposing corporate reputation to long-term risks. This dynamic affects not only individual consumer-brand relationships but also the broader structure of market competition and the social fabric.

The impact of algorithms on consumer trust is not only a technical issue but is also noteworthy for its social and psychological dimensions. Non-transparent algorithmic processes reinforce consumers' sense of loss of control over these systems and accelerate the erosion of trust (Dezao, 2024).

In terms of corporate reputation, the effects of algorithms should be examined across a spectrum that encompasses both short-term operational outcomes and long-term strategic positioning. Scandals caused by biased or manipulative algorithms can lead to reputational damage by identifying brands with unethical practices. Moreover, the potential for algorithms to reinforce systemic inequalities exposes businesses to individual consumer backlash and societal criticism (Koene, 2017). In this context, the impact of algorithms on consumer trust and corporate reputation emerges as an area that tests not only the technological competencies of businesses but also their ethical stance and social responsibilities, which necessitates algorithmic governance to become a strategic priority.

3.1. Loss of Trust

The destructive impact of algorithmic biases on consumer trust is a powerful dynamic resulting from perceived unfairness and lack of transparency. The inaccurate price predictions of Zillow's iBuying algorithm, for example, not only led to financial losses but also raised serious doubts about the reliability of artificial intelligence, clearly demonstrating the fragility of algorithms and their psychological impact on consumers (Susarla, Purnell, & Scott, 2024). Similarly, the systematic exclusion of communities of colour by race-based ad targeting has caused an intense consumer backlash against brands and shaken the foundation of trust (McIlwain, 2023). Lack of transparency further complicates this process; consumers feel manipulated or neglected when they do not understand decision-making processes (Dezao, 2024). Such incidents show that businesses need to design algorithmic systems in a way that is not only compatible with technical accuracy but also with consumer perceptions and ethical norms; otherwise, loss of trust can lead to irreversible erosion of customer loyalty and market share.

3.2. Reputation Risks

The impact of algorithms on corporate reputation is dramatically manifested by the blows to brand perception caused by unethical practices and manipulative campaigns. While such incidents lead to sales losses in the short term, they trigger reputational erosion in the long term, permanently weakening the perception of the credibility of brands (Akter et al., 2022). Moreover, the distortions created by algorithms in market competition create an environment where large players gain unethical advantages, especially by disadvantaging small businesses (Csurgai-Horváth, 2024). This dynamic exposes businesses to individual consumer backlash and an industry-wide wave of ethical questioning, suggesting that algorithmic strategies should be evaluated not only from a profitability perspective but also from a reputational capital perspective. Reputational risks are thus becoming a central element in the strategic planning of businesses.

3.3. Social Impacts

The societal impacts of algorithms encompass a domain where bias and personalised content transcend individual consumer experiences to become a force shaping the social fabric. The disinformation amplification of biased algorithms exacerbates social polarisation by creating echo chambers that reinforce users' existing beliefs; this systematically undermines the capacity for dialogue and compromise (Shin, 2024). More importantly, the potential for algorithms to reinforce systemic inequalities leads to the reproduction of historical injustices in the digital age, suggesting that the societal consequences of AI are not merely a side effect but a fundamental design issue (Koene, 2017). These impacts shift the responsibility of businesses from being limited to the consumer to a broader social context; algorithms are thus positioned as both a technological tool and a social actor. When businesses ignore these impacts, they risk their reputation and social legitimacy, a caveat that necessitates an ethical and inclusive framing of algorithmic design.

4. Solution Suggestions

The biases of algorithms in marketing strategies and their adverse effects on consumer trust and corporate reputation require businesses and academics to develop comprehensive and multidimensional solutions. These solutions range from technical innovations to ethical principles and regulatory frameworks, as the risks of algorithmic systems are not limited to data processing or model design but extend to broader areas such as social dynamics and organisational legitimacy. The literature suggests that such approaches can go beyond reducing bias and increase algorithms' transparency, improve consumer perceptions and strengthen brand credibility in the long run (Chen, 2024; Rebitschek, 2024). The proposed solutions offer a strategic framework combining operational efficiency and ethical responsibility in this context.

The resolution of algorithmic biases is a technical issue and an endeavour for businesses to rebuild trust in their relationship with consumers and maintain their social acceptability. While technical solutions aim to reduce bias through, for example, fair data processing methods, ethical frameworks enshrine fairness and privacy as fundamental principles in the design of algorithms (Soni, 2024). However, the success of these efforts depends on being supported by international regulatory standards that go beyond the capacity of individual businesses, with examples such as the GDPR and the EU Artificial Intelligence Act proving to deliver tangible advances in data privacy and transparency (Al-Haj Eid et al., 2024; Hulicki, 2023). This tripartite structure - technical, ethical and regulatory - has the potential to systematically minimise the risks of algorithms while preserving their potential advantages.

From a broader perspective, the proposed solutions developed for algorithms have the power to shape the future role of AI beyond addressing current problems. By implementing these solutions, businesses can reverse the loss of trust and reputational erosion caused by biased systems; in the process, they can seize the opportunity to establish a more transparent and fair relationship with consumers (Bar-Gill, Sunstein, & Talgam-Cohen, 2023).

4.1. Technical Solutions

Addressing algorithmic bias at a technical level requires innovative strategies ranging from data handling processes to model design; this is a key element in improving the fairness and effectiveness of marketing practices. Fair data processing methods, such as resampling and using metrics such as Differential Impact (DI), can prevent discrimination by correcting imbalanced data sets; these techniques produce more inclusive results by intervening in the source of bias (Soni, 2024). In addition, explainable AI (XAI) presents algorithmic processes transparently to consumers through tools such as decision trees; this not only strengthens trust but also increases the accountability of businesses (Chen, 2024). These technical solutions emphasise that algorithms should be developed not only with a focus on accuracy and efficiency but also with an ethical and consumer-oriented approach so businesses can maximise their technological advantages while minimising the risks of bias.

4.2. Ethical Frameworks

Ethical frameworks aim to reverse the adverse effects of bias on consumer trust by establishing fairness, privacy and transparency as fundamental principles in the design and implementation of algorithms. Transparency restores trust by clearly explaining the workings of algorithms to consumers, which is especially critical in situations where perceptions of privacy violations are widespread (Rebitschek, 2024). On the other hand, ethical design prioritises privacy and fairness principles from the outset of the development process, ensuring that algorithms function in line with technical performance and societal values (Sharma & Sharma, 2023). These frameworks require businesses to meet legal requirements, consumer expectations, and ethical standards so that algorithms can move from being a risk factor to an indicator of corporate responsibility.

4.3. Regulatory Approaches

Regulatory approaches aim to ensure consumer protection and organisational accountability by providing international standards and cooperation mechanisms to address the systemic effects of algorithmic biases. Regulations such as the GDPR put data privacy in a strong framework (Al-Haj Eid et al., 2024), while the EU Artificial Intelligence Act reduces the societal risks of algorithmic systems by mandating transparency and ethical practices (Hulicki, 2023). However, the success of these regulations relies on collaboration between AI developers, ethicists, and regulators; this multidisciplinary approach generates holistic solutions by considering not only the technical but also the societal dimensions of biases (Bar-Gill, Sunstein, & Talgam-Cohen, 2023). This regulatory vision allows businesses to move towards fairer and more transparent algorithmic practices while maintaining a competitive advantage in global markets, thus balancing algorithms as both a source of innovation and an area of social responsibility.

Conclusion

The rise of artificial intelligence (AI) algorithms in digital marketing has opened up a unique competitive space for businesses by enhancing individualised campaigns and data-driven decision-making capabilities (Gupta, 2024). However, this study reveals that algorithmic biases create ethical and practical cracks in marketing strategies. Through a systematic literature review, it has been confirmed that AI systems have the potential to discriminate based on sensitive factors such as race, gender, and socioeconomic status; these biases have been observed to either exclude or falsely target specific social clusters in segmentation processes (Pappadà & Pauli, 2023; Bigman et al., 2023; Soni, 2024). This undermines the effectiveness of marketing campaigns, erodes consumer trust, and can jeopardise organisational legitimacy. This chapter argues that the transformative power of AI can only be fully realised when it is free from these shadows.

The origins of algorithmic biases are characterised by systematic distortions in educational data, deficiencies in design decisions and dynamics shaped by socio-cultural contexts (Singh, 2023). Findings reveal that these biases are not mere technical failures; on the contrary, they function as a powerful catalyst that deepens social inequalities (McIlwain, 2023). For example, discriminatory practices of personalised advertising algorithms towards low-income communities create long-term threats to brand loyalty while fuelling consumer dissatisfaction; this undermines the principle of equal access, the fundamental promise of marketing (Parasrampuria & Williams, 2023). Moreover, the lack of transparency in algorithmic decision-making paralyses accountability mechanisms and calls into question the ethical obligations of businesses (Nazeer, 2024). This clearly shows that AI is a tool and a reflection of societal values.

In this context, placing AI in digital marketing on an ethical footing requires an urgent and multi-layered intervention. While technical strategies to eliminate biases - such as justice-oriented data processing techniques and explainable AI models - form the cornerstones of the solution (Soni, 2024; Chen, 2024), international standards and regulatory frameworks support these efforts with an institutional discipline (Hulicki, 2023). While regulations such as GDPR provide a solid foundation for data privacy protection, the need for more inclusive guidelines based on algorithmic fairness and transparency is evident (Sharma & Sharma, 2023; Adams-Prassl et al., 2024). Businesses should prioritise strategic investments in ethical AI practices to restore consumer trust and maintain competitive advantage (Yadav, 2024). This is not only an operational imperative but also a moral imperative for marketing to evolve into a future aligned with social responsibility.

In conclusion, algorithmic biases present both a threat and an opportunity as a dilemma shaping the future of digital marketing. This study argues that in order to harness the transformative potential of AI fully, it is essential that ethical and technical dimensions are addressed together; this requires a delicate balance between innovation and fairness. Future research should strengthen this balance by examining the practical applications of bias reduction techniques and their long-term effects on consumer perception (Vasileva, 2020). Thus, marketing strategies can become a field that appeals to all segments by harmonising technological progress with social welfare.

It should not be forgotten that digital marketing is not only a commercial discipline but also a mirror of social structures. If not framed ethically, the advantages of personalisation and automation offered by AI risk institutionalising discrimination and undermining trust. For example, the systematic exclusion of minority groups in audience identification processes not only narrows the consumer base but also jeopardises the long-term reputation of companies (Bigman et al., 2023).

References

Akter, Shahriar, Yogesh K. Dwivedi, Shahriar Sajib, Kumar Biswas, Ruwan J. Bandara, ve Katina Michael. 2022. "Algorithmic Bias in Machine Learning-Based Marketing Models". Journal of Business Research 144: 201-16. doi:10.1016/j.jbusres.2022.01.083.

Al Haj Eid, Mohammad, Mohammad Abu Hashesh, Abdel-Aziz Ahmad Sharabati, Ahmad Khraiwish, Shafig Al-Haddad, ve Hesham Abusaimeh. 2024. "Conceptualizing Ethical AI-Enabled Marketing: Current State and Agenda for Future Research". doi:10.20944/preprints202404.0786.v1.

Babadoğan, Borga. 2024. "Unveiling the Power of AI-Driven Personalization: Transforming Consumer Behavior in the Age of Digital Marketing". Next Frontier For Life Sciences and AI 8(1): 61. doi:10.62802/fj43xy18.

Bar-Gill, Oren, Cass R. Sunstein, ve Inbal Talgam-Cohen. 2023. "Algorithmic Harm in Consumer Markets". SSRN Electronic Journal. doi:10.2139/ssrn.4321763.

Barat, Ayan, ve Krity Gulati. 2024. "Emergence of AI in Marketing and its Implications". Lloyd Business Review: 1-24. doi:10.56595/lbr.v3i1.22.

Berbeglia, Franco, Gerardo Berbeglia, ve Pascal Van Hentenryck. 2021. "Market Segmentation in Online Platforms". doi:10.48550/arXiv.1511.00750.

Bigman, Yochanan E., Desman Wilson, Mads N. Arnestad, Adam Waytz, ve Kurt Gray. 2023. "Algorithmic Discrimination Causes Less Moral Outrage than Human Discrimination." Journal of Experimental Psychology: General 152(1): 4-27. doi:10.1037/xge0001250.

Boyko, Bogdan, ve Irina Protsik. 2024. "USE OF CLUSTERING ALGORITHMS TO SEGMENT THE COMPANY'S PERSONNEL". Herald of Khmelnytskyi National University. Technical sciences 333(2): 92-98. doi:10.31891/2307-5732-2024-333-2-14.

Chen, Changdong. 2024. "How Consumers Respond to Service Failures Caused by Algorithmic Mistakes: The Role of Algorithmic Interpretability". Journal of Business Research 176: 114610. doi:10.1016/j.jbusres.2024.114610.

Csurgai-Horváth, Gergely. 2024. "Regulating Algorithmic Bias as a Key Element of Digital Market Regulation". World Competition 47(Issue 2): 193-212. doi:10.54648/WOCO2024015.

Dezao, Tara. 2024. "Enhancing Transparency in AI-Powered Customer Engagement". Journal of AI, Robotics & Workplace Automation 3(2): 134. doi:10.69554/PPJE1646.

Dwivedi, Y. 2024. "AI Virtual Assistants in Human Services: Empowering Customers and Caseworkers". International Jurnal Of Scientific Research in Engineering and Management 08(11): 1-7. doi:10.55041/IJSREM37870

Elkhatibi, Yassine, ve Redouane Benabdelouhed. 2024. “Digital Revolution: How AI is Transforming Content Marketing”. International Journal of Advanced Multidisciplinary Research and Studies 4(5): 775-77. doi:10.62225/2583049X.2024.4.5.3324.

Gladden, James M., George R. Milne, ve Mark A. McDonald. 2015. “Biases in Self-Reports of Zip Codes and Zip +4 in(Pappadà ve Pauli 2022) Geodemographic Segmentation”. Içinde Proceedings of the 1997 World Marketing Congress, Developments in Marketing Science: Proceedings of the Academy of Marketing Science, ed. Samsinar Md Sidin ve Ajay K. Manrai. Cham: Springer International Publishing, 85-94. doi:10.1007/978-3-319-17320-7_23.

Goankar, Bilwaj, Kirstin Cook, ve Luke Macyszyn. 2020. “Ethical Issues Arising Due to Bias in Training A.I. Algorithms in Healthcare and Data Sharing as a Potential Solution”. AI Ethics Journal 1(2). doi:10.47289/AIEJ20200916.

Guhl, Daniel, Katharina Dowling, Daniel Klapper, Martin Spann, Lucas Stich, ve Narine Yegoryan. 2020. “Behavioral Biases in Marketing”. Journal of the Academy of Marketing Science 48(3): 449-77. doi:10.1007/s11747-019-00699-x.

Gupta, Dr. Ruchi. 2024. “The impact of Artificial intelligence on Marketing Strategies: A Comprehensive Analysis”. International Journal for Research in Applied Science and Engineering Technology 12(11): 270-71. doi:10.22214/ijraset.2024.65002.

Hera, Octavian Dumitru. 2024. “Exploring Marketing Transformation in the Age of Artifical Intelligence”. Journal of Financial Studies 9(Special): 96-108. doi:10.55654/JFS.2024.9.SP.07.

Huang, Yijun, Qiteng Chen, Lie Luo, ve Zhongyan Lin. 2024. “Algorithmic Discrimination and Market Competition: Exploring the Ethical and Legal Issues of Algorithm Management by Internet Companies”. Philosophy and Social Science 1(5): 22-27. doi:10.62381/P243504.

Hulicki, Maciej. 2023. “The principles of algorithmic justice in the digital market”. İçinde Research Handbook on Digital Trade, ed. David Collins ve Michael Geist. Edward Elgar Publishing, 345-68. doi:10.4337/9781800884953.00032.

Ji, Luo. 2003. “Market Segmentation Research: Critical Review and Perspectives”. Journal of Shandong University.

Koene, Ansgar. 2017. “Algorithmic Bias: Addressing Growing Concerns [Leading Edge]”. IEEE Technology and Society Magazine 36(2): 31-32. doi:10.1109/MTS.2017.2697080.

Lambrecht, Anja, ve Catherine E. Tucker. 2016. "Algorithmic Bias? An Empirical Study into Apparent Gender-Based Discrimination in the Display of STEM Career Ads". SSRN Electronic Journal. doi:10.2139/ssrn.2852260.

Liu, Bingyuan, Jose Dolz, Adrian Galdran, Riadh Kobbi, ve Ismail Ben Ayed. 2024. "Do We Really Need Dice? The Hidden Region-Size Biases of Segmentation Losses". Medical Image Analysis 91: 103015. doi:10.1016/j.media.2023.103015.

Liu, Jinwen. 2024. "Marketing Strategy Matching Algorithm Under Artificial Intelligence". İçinde 2024 Third International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE), Ballari, India: IEEE, 1-5. doi:10.1109/ICDCECE60827.2024.10548817.

Mandić, Antonija, Biljana Marković, ve Ana Mulović Trgovac. 2024. "Tools of Artificial Intelligence Technology as a Framework for Transformation Digital Marketing Communication". Tehnički glasnik 18(4): 660-65. doi:10.31803/tg-20240708161118.

Martin, S.K., ve A.C. Zwart. 1987. "MARKETING AGENCIES AND THE ECONOMICS OF MARKET SEGMENTATION*". Australian Journal of Agricultural Economics 31(3): 242-55. doi:10.1111/j.1467-8489.1987.tb00467.x.

McIlwain, Charlton D. 2023. "Algorithmic Discrimination: A Framework and Approach to Auditing & Measuring the Impact of Race-Targeted Digital Advertising". SSRN Electronic Journal. doi:10.2139/ssrn.4646843.

Moussawi, Sara, Xuefei (Nancy) Deng, ve K. D. Joshi. 2024. "AI and Discrimination: Sources of Algorithmic Biases". ACM SIGMIS Database: the DATABASE for Advances in Information Systems 55(4): 6-11. doi:10.1145/3701613.3701615.

Oleg Ye., Backsanskiy. 2025. "Balancing Ethics and Innovation in Artificial Intelligence". Society: philosophy, history, culture (1): 23-33. doi:10.24158/fik.2025.1.2.

Panda, Amiya Ranjan, Priyanka Rout, ve Aman Gautam. 2024. "Optimizing Marketing Strategy by Performing Customer Segmentation". İçinde 2024 International Conference on Advances in Computing Research on Science Engineering and Technology (ACROSET), Indore, India: IEEE, 1-6. doi:10.1109/ACROSET62108.2024.10743643.

Pappadà, Roberta, ve Francesco Pauli. 2022. "Discrimination in machine learning algorithms". doi:10.48550/ARXIV.2207.00108.

Parasrampuria, Anirudh, ve Katherine Williams. 2023. "Ethical Considerations and Societal Impact of Personalized Advertising Algorithms". Journal of Student Research 12(4). doi:10.47611/jsrhs.v12i4.5910.

Pasupuleti, M.K. 2024. "Transforming Digital Marketing with AI: Strategies for Personalized Content and Ethical Advertising". İçinde AI in Digital Marketing: Personalizing Content and Advertising Strategies, National Education Services, 1-18. doi:10.62311/nesx/66296.

Potluri, Chandra Srinivas, G. Srinivasa Rao, L.V.R Manoj Kumar, Kedir Geletu Allo, Yaregal Awoke, ve Abdilkerim Asrar Seman. 2024. "Machine Learning-Based Customer Segmentation and Personalised Marketing in Financial Services". İçinde 2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE), Gautam Buddha Nagar, India: IEEE, 1570-74. doi:10.1109/IC3SE62002.2024.10593143.

Rathnow, Peter, Benjamin Zeller, ve Matthias Lederer. 2024. "From Code to Coin: Unravelling the Practical Business Impact of Algorithmic Pricing". Journal of AI, Robotics & Workplace Automation 3(3): 234. doi:10.69554/YMZP4012.

Rebitschek, Felix G. 2024. "Boosting Consumers: Algorithm-Supported Decision-Making under Uncertainty to (Learn to) Navigate Algorithm-Based Decision Environments". Içinde Knowledge and Digital Technology, Knowledge and Space, ed. Johannes Glückler ve Robert Panitz. Cham: Springer Nature Switzerland, 63-77. doi:10.1007/978-3-031-39101-9_4.

Reddy, Biyyapu Sri Vardhan, C. A. Rishikeshan, VishnuVardhan Dagumati, Ashwani Prasad, ve Bhavya Singh. 2024. "Customer Segmentation Analysis Using Clustering Algorithms". Içinde Intelligent Systems, Lecture Notes in Networks and Systems, ed. Siba K. Udgata, Srinivas Sethi, ve Xiao-Zhi Gao. Singapore: Springer Nature Singapore, 353-68. doi:10.1007/978-981-99-3932-9_31.

Samala, Agariadne Dwinggo, ve Soha Rawas. 2025. "Bias in artificial intelligence: smart solutions for detection, mitigation, and ethical strategies in real-world applications". IAES International Journal of Artificial Intelligence (IJ-AI) 14(1): 32. doi:10.11591/ijai.v14.i1.pp32-43.

Sarkar, Malay, Aisharyja Roy Puja, ve Faiaz Rahat Chowdhury. 2024. "Optimizing Marketing Strategies with RFM Method and K-Means Clustering-Based AI Customer Segmentation Analysis". Journal of Business and Management Studies 6(2): 54-60. doi:10.32996/jbms.2024.6.2.5.

Sharma, Animesh Kumar, ve Rahul Sharma. "Considerations in Artificial Intelligence-Based Marketing: An Ethical Perspective". Applied Marketing Analytics: The Peer-Reviewed Journal 9, sy 2 (01 Ekim 2023): 162. https://doi.org/10.69554/RAPQ3226.

Shin, Donghee. 2024. "Misinformation and Algorithmic Bias". Içinde Artificial Misinformation, Cham: Springer Nature Switzerland, 15-47. doi:10.1007/978-3-031-52569-8_2.

Singh, Daman Preet. 2023. "Algorithmic Bias of Social Media". The Motley Undergraduate Journal 1(2). doi:10.55016/ojs/muj.v1i2.77457.

Soni, Vishvesh. 2024. "Bias Detection and Mitigation in AI-Driven Target Marketing: Exploring Fairness in Automated Consumer Profiling". International Journal of Innovative Science and Research Technology (IJISRT): 2574-84. doi:10.38124/ijisrt/IJISRT24MAY2203.

Susarla, Padma, Dexter Purnell, ve Ken Scott. 2024. "Zillow's Artificial Intelligence Failure and Its Impact on Perceived Trust in Information Systems". Journal of Information Technology Teaching Cases: 20438869241279865. doi:10.1177/20438869241279865.

Susarla, Padma, Dexter Purnell, ve Ken Scott. 2024. "Zillow's Artificial Intelligence Failure and Its Impact on Perceived Trust in Information Systems". Journal of Information Technology Teaching Cases: 20438869241279865. doi:10.1177/20438869241279865.

Tang, Zicheng. 2024. "The Role of AI and ML in Transforming Marketing Strategies: Insights from Recent Studies". Advances in Economics, Management and Political Sciences 108(1): 132-39. doi:10.54254/2754-1169/108/20242009.

Van Basshuysen, Philippe. 2023. "Markets, Market Algorithms, and Algorithmic Bias". Journal of Economic Methodology 30(4): 310-21. doi:10.1080/1350178X.2022.2100919.

Vasileva, Mariya I. 2020. "The Dark Side of Machine Learning Algorithms: How and Why They Can Leverage Bias, and What Can Be Done to Pursue Algorithmic Fairness". Içinde Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, Virtual Event CA USA: ACM, 3586-87. doi:10.1145/3394486.3411068.

Wang, Weihan. 2024b. "Artificial Intelligence in Strategic Business Decisions: Enhancing Market Competitiveness". Advances in Economics, Management and Political Sciences 117(1): 87-93. doi:10.54254/2754-1169/117/20241987.

Yadav, Suraj Jaywant. 2024. "AI Bias and Fairness: Ethical Considerations in Service Marketing Strategies". IGI Global, 49-64. doi:10.4018/979-8-3693-7122-0.ch003.

Chapter 6

The Misleading Power of AI-Powered Automation

Ali Sen[1]

Abstract

Automation refers to the use of technology that attempts to perform a procedure or process without human intervention. Automation technologies aim to minimise human intervention and increase factors such as efficiency, productivity, quality, and accuracy. While Artificial Intelligence (AI)-supported automation solutions offer many advantages for users such as customisation, recommendation systems and content creation, they also pose risks such as biased algorithms or data privacy concerns. Despite the growing use of AI-supported automation systems in the marketing, insufficient studies mention the risks posed by AI-powered automation systems.

The purpose of this study is to investigate how automation systems are used in marketing by examining existing research and cases. This study shows how to improve the customer experiences and highlights the risks that can lead to consumer dissatisfaction if misconfigured. Using these technologies can unintentionally cause certain biases. Two issues stand out in the use of these technologies: Automation bias and algorithmic bias. The first, automation bias, is associated with users' overconfidence in automation systems, while the second, algorithmic bias, refers to misleading effects based on data sets. This study provides insight into the risks posed by automation efforts, as well as some suggestions for building consumer trust in marketing.

Automation means the use of technology that attempts to perform a procedure or a process without human intervention. A typical automated system includes three basic elements. A power source to operate the system, a program of instruction and a control system (Groover, 2018). The overall aim of automation technologies is to minimise human intervention and to increase factors such as efficiency, productivity, quality and reliability. (Goldberg, 2011; Sing & Namekar, 2020). Looking at the history of

1 PhD Lecturer, University of Istanbul, ali.sen@istanbul.edu.tr, ORCID ID

https://doi.org/10.58830/ozgur.pub710.c3023

automation, it has been shaped by the replacement of manual labour with machinery, and today it has evolved from simple devices to computer-based technology (Hitomi, 1994; Jasnssen et al., 2019). This historical journey dates back to four million years. It traces back to the beginning of human beings using simple tools and the beginning of developments in production (Hitomi, 1994). Many of today's automation systems are integrated with Artificial Intelligence (AI)-supported systems (Maedche et al., 2019; Van Esch et al., 2021) (Maedche et al., 2019; Van Esch et al., 2021). The transformation to artificial intelligence (AI)-assisted automation has offered great opportunities to improve user experiences or increase efficiency in business processes in many areas (e.g. Huseynov, 2023; Mirwan, 2023). (e.g. Huseynov, 2023; Mirwan, 2023).

While AI-supported automation solutions offer many advantages for users such as customisation, recommendation systems and content creation, they also pose risks such as biased algorithms or data privacy concerns (Farbo & Shiva, 2024; Palanque et al., 2019; Wertenbroch, 2019). Given that algorithms are developed based on historical data or specific data sets, they may further reinforce pre-existing prejudices in society (Karami et al., 2024). This may lead to discriminatory or marginalising marketing strategies targeting disadvantaged groups such as gender, race, social status, economic status, etc (Madanchian, 2024).

Biased algorithms can lead to inaccurate assessments not only in marketing but also in other areas such as customer-specific recommendation programs, credit scores and health (Mehrota et al., 2023). These types of biased systems can cause consumers to perceive automation-based marketing practices as unfair or biased, which can negatively impact brand trust and reputation. The lack of transparency in these technologies can lead to injustice by damaging consumer trust (Madanchian, 2024; Lepri et al., 2018). Therefore, it is important to know and understand the biases introduced by automation systems to make the personalization more applicable in marketing applications and to fully understand customer experiences (Akter et al., 2023).

The purpose of this study is to investigate how automation systems are used in marketing to improve the customer experience and to highlight the risks that can lead to consumer dissatisfaction if misconfigured. Thanks to technological advances, customers can evaluate the benefits or risks offered by technology during the purchasing process. For example, while robotic process automation can improve customer satisfaction by increasing a company's efficiency, the customer experience can suffer if automation is implemented incorrectly (Gavrilla et al., 2023). In this study, firstly, some automation systems that improve the consumer experience will be introduced, and then the misleading effects of automation technologies and the problems that arise in the interaction with the consumer will be examined.

1. Consumer Experiences and Automation Solutions

In this section, some automation technologies improving customer experience will be mentioned for a better understanding of the subject. Instead of mentioning all technologies, the customer experience of some of the systems in the field of marketing will be emphasised.

1.1. Chatbots

A chatbot is designed to mimic human speech. These systems utilise predetermined rules and machine learning algorithms to correctly interpret and respond to user input. They use Natural Language Processing (NLP) technology in this process (Huseynov, 2023). The idea of the first conversational robot emerged in 1950 when computer scientist Alan Turing wondered whether computers could speak like humans (Adamopoulou & Moussiades, 2020). Over time, different chatbots have been developed. For example, "Eliza" (1966), "Parry" (1972), "Jabberwacky" (1988), "TinyMUD" (1991), "ALICE" (1995).", In 2001, chatbots were further developed and the SmarterChild chatbot was introduced, which could interact with users and contribute to non-formal learning (Molnár & Zoltán, 2018).

Today's chatbots are further enhanced by generative pre-trained models (Generative Pre-trained Transformers, GPT). ChatGPT developed by OpenAI (Huseynov, 2023); Microsoft's Bing chatbot, Bard developed by Alphabet, and Baidu's Ernie model (Yıldıran & Erdem, 2024), are among today's advanced chatbots. These artificial intelligence-supported systems will continue to develop as new versions are released. Artificial Intelligence (AI)-based chatbots improve the user experience with features such as instant response, personalised answers and 24/7 service. These robots provide great simplicity in reservation processes such as car rentals, accommodation and flights, and are widely used in customer service and sales sectors. Users recognise the ease with which chatbots can instantly respond to inquiries and provide quick information. They also reduce the staffing needs of businesses by managing multiple customer requests (Huseynov, 2023).

In addition to improving the customer experience, AI-powered chatbots can offer fully customised responses by leveraging machine learning algorithms. This situation increases consumer loyalty by keeping user satisfaction at a high level (Huseynov, 2023). Through chatbots, customers can get personalised support by contacting chatbots directly instead of browsing e-commerce sites, thus saving time and effort. In addition, data from the interaction of chatbots with the customer provides insights into the needs of customers and improves the customer experience (Huseynov, 2023).

Furthermore, the study on the usability of chatbots indicated that these technologies have a significant positive impact on the extrinsic value of the customer experience (e.g. convenience, time) (Kokkinou and Cranage, 2013). Users find companies that use chatbots innovative (Chen et al., 2021). On the other hand, problems such as lack of expertise and lack of context awareness hinder the development of chatbots (Pricilla et al., 2018). This leads to chatbots offering negative user experience to be perceived negatively and evaluated as a time-wasting process (Chen et al., 2021).

In summary, chatbots can be defined as an AI-powered or rule-based technology that provides 24/7 customer support and attempts to solve basic questions or simple problems without human intervention (Castillo et al., 2021). They can offer a personalised interaction by leveraging past interactions and data from user profiles. This reduces the workload and costs of customer service agents by automating routine tasks.

1.2. Recommender Systems

Another method used in marketing to improve the user experience is to recommend content or products to customers. Recommender systems with AI-powered recommender systems are designed to provide alternatives, make suggestions and evaluate real scenarios by collecting information from data to address users' problems or questions (Xu et al., 2020).

Recommender systems developed to improve user experience can be divided into two main categories. These systems are traditional recommender systems and automated recommender system (Yang et al., 2021). Traditional recommender systems collect user preferences in the form of implicit feedback. These include purchase behaviour (Su and Khoshgoftaar, 2000), click-through rate (Zhou et al., 2018), collaborative filtering (Shi et al., 2014) or neural networks (He et al., 2017) to build latent spaces for user preferences. Whereas, automated recommendation systems base their recommendation on users' preferences derived directly from live dialogue history (Yang et al., 2021). These systems aim to interact with users to provide them with the desired product (e.g. consumer goods, films, music) or service.

Sectors such as e-commerce (Maedche et al., 2019; Yang et al., 2021), entertainment (Palangue et al., 2019) and marketing (Rae et al., 2016) commonly utilise AI-enabled automated recommender systems. Companies such as Amazon, Netflix, Starbucks, Spotify, and Alibaba offer personalised products tailored to consumers by examining their past purchasing behaviour, searches and browsing history (Mirwan, 2023). Spotify's recommendation system analyses millions of songs and users' listening habits to provide a weekly playlist personalized for users (Florez Ramos & Blind, 2020; Mirwan, 2023). Thanks to suggestion systems, users can easily access the content they want without excessive time and effort and improve the customer experience.

Digital assistants with recommender systems reduce users' cognitive load. When users are exposed to excessive information, recommender systems help them sort, filter and process relevant information. E-commerce sites allow the consumer to easily find the product or service they are looking for without the need for extensive research (Maedche et al., 2019). Similarly, companies such as Netflix, Amazon, Outbrain, Tabollaa, etc. also use content or product recommendation systems to provide users with a choice that may be of interest to them. Thus, these systems save users from searching extensively (Andre et al., 2018).

1.3. Automated Email and Messaging Systems

Email is one of the most widely used tools for communication, both professionally and personally. For an individual or an organisation, communicating via email and receiving a quick response can significantly improve the customer experience. Using automated email responses is a good way for an organisation to respond to an email recipient within 24 hours, especially when an email cannot be responded to within 24 hours due to holidays, workload or leave of absence (Mane & Rayappa, 2022).

Besides individual communication, e-mail also plays an extensive role in the workplace. It is used in the workplace not only as a communication tool but also as a work hub. Studies have shown that e-mail serves as the main interface in the workplace, providing facilities for planning activities, organising meetings, transferring files and more (Ducheneaut & Bellotti, 2001). Automated email, also known as behaviour-driven email, refers to the sending of personalised messages in a predetermined and automated manner based on an action that a customer or user takes (or does not take) (Vaughan, 2012). Email automation saves time by creating targeted, contextualised and personalised emails to send to the relevant recipient. For example, after a customer purchases a product, a personalised e-mail can be sent to the customer saying 'Check out other products similar to the ones you bought' (Vaughan, 2012). Similarly, a consumer who buys a product from an e-commerce platform can be sent an automated e-mail about the progress of the order (Kushmerick et al., 2015).

Today, business life is closely related to e-mail and a significant part of the employees' day is spent using e-mail (Grevet et al., 2014). Therefore, there has long been a desire to automate various aspects of this process because of the workload generated by e-mail. These efforts date back to Procmail, an email filtering program released in 1990 that allowed users to automatically send certain mail to certain folders (Park et al., 2019). Similarly, the Boomerang application saves users time by eliminating difficulties caused by back-and-forth email traffic, time zone conflicts, and errors due to double bookings. In addition, it has features such as creating automatic reservations, sharing availability, and offering time suggestions for meetings (www.boomeranggmail.com; Park et al., 2019). Such automation tools optimize business processes and improve user experience.

As a result, for businesses, automating repetitive emails allows employees to focus on more strategic tasks and analysis-oriented tasks. It allows them to respond to customers faster (Kushmerick, 2005). Furthermore, automated e-mail systems integrated with AI can improve the user experience by providing customised solutions to specific customers. As a result, while increasing customer satisfaction, it can also positively affect sales in terms of e-commerce (Abrokwah-Larbi et al., 2024; Ghalme et al., 2023).

1.4. Robotic Process Automation (RPA)

With the advent of the fourth industrial revolution, the use of data from smart devices has enabled the automation of ordinary rule-based business processes with Robotic Process Automation (RPA) tools (Ribeiro et al., 2021). Robotic process automation is a technology that mimics human interactions through graphical user interfaces and automates business processes based on user and system interactions (König et al. 2020). In corporations, this technology is trained to perform repetitive tasks, automating existing business processes and making them more efficient (Karn et al. 2019). For example, the telecommunications company O2 has automated a large part of its customer service. Processes such as SIM card replacement, mobile number porting, phone unlocking and switching to contract lines have been automated through robotic processes. Being able to fulfil customer service requests shows how robotic processes can be trained and make business processes more efficient by reducing human intervention (Madakam et al., 2019). This reduces costs and errors in the workplace and provides continuous accessibility for customers (Daase et al., 2020).

Through technological growth, users can identify the benefits and risks of technology in their purchasing process. In particular, RSO can increase consumer satisfaction and engagement by improving efficiency and agility in an organisation (Gavrilla et al., 2023). Recent studies report that the implementation of RSO is efficient in terms of error reduction, cost reduction and efficiency (Aguirre and Rodriguez 2017). RSO technology allows many business processes to be facilitated and this allows employees to work more effectively and make fewer mistakes (Madakam et al., 2019). By automating repetitive processes, for example, banks devote more resources to personalised customer service. This increases the chances of responding more quickly to customer enquiries and requests (Lakshmi et al., 2024).

2. Biases in Automation Technologies

Automation systems have a significantly positive impact on marketing professionals and customers. However, using these technologies can unintentionally cause some prejudices. Two issues stand out in the use of these technologies. Automation bias and algorithmic bias. The first is automation bias, which is associated with the overconfidence of users in automation systems, while the second is algorithmic bias, which is the misleading effects based on data sets. Therefore, customers or experts need to be more careful when making decisions based on automation systems to use these technologies correctly.

2.1. Recognizing Automation Bias

Automation bias is defined as the tendency to over-reliance on automated systems even though it may lead to incorrect decisions. (Goddard et al., 2012). Automation bias is similar to the biases of individuals in decision-making processes. According to social psychologists, individuals mostly make intuitive decisions in their daily lives. Intuitive decision making is to make inferences quickly and simply. That is, when faced with information overload, the individual aims to reach a conclusion quickly and make a reasonably correct decision (Kupfer et al., 2023; Parasuraman & Riley, 1997). Relying on automated support tools offers a more accessible and acceptable way for individuals. Faced with information overload, individuals often tend to avoid complex processes (Mosier & Skitka, 2018). Automation bias and its negative consequences have been studied in many contexts such as health, military processes, personnel selection and process control (Kupfer et al., 2023). This can occur in any area where there is human-system interaction (Goddard et al., 2012). For example, in critical areas such as aircraft cockpits and nuclear power plants, the use of automated decision support tools is common. This situation enables people to make decisions quickly and easily because they want to make less cognitive effort (Mosier & Skitka, 2018).

When the literature is analysed, two types of errors usually occur in decision-making technologies that rely on automation. The first is omission errors. This means that when automation systems work incorrectly or fail to recognise a problem, people overlook it. The second one is the so-called commission errors. In this case, people follow incorrect advice and instructions from automated systems, even though they contradict other information or without checking alternative information (Skitka et al., 2000). For example, some organisations use AI-enabled tools to screen CVs during the recruitment process. AI tools screen candidates by looking at their CVs or other important points. However, under time pressure, HR staff accept these recommendations without a detailed scrutiny. This is an example of automation bias because HR staff may accept the AI algorithm as reliable and ignore the errors of the system.

Automation bias is thought to be related to individuals' intuitive behaviour instead of examining information carefully. There are various reasons for this situation in the literature. According to Skitka (1990), the first one is cognitive laziness. People tend to avoid cognitive effort as much as possible. They prefer intuitive approaches that require the least cognitive effort rather than thinking about every detail when making decisions. This tendency is associated with individuals relying on automation without validation, especially when their tasks are extremely difficult and complex (Danelid, 2024). The second is the social loafing factor. Individuals are more lazy in group work because they share their responsibilities with others (Karau & Williams, 1993). This situation is also seen in human-computer interaction. Individuals may perceive automation systems as a team mate and may take less responsibility and make less effort. The third factor is the human tendency to obey authority. Automated systems are perceived as an authority because they reduce user errors. From this point of view, when individuals are faced with the information proposed by automation systems, they tend to accept it without questioning.

Automation bias has also been analysed from different perspectives in the literature. One of these approaches is that individuals tend to rely on first information when people make decisions. When working with automated decision systems, individuals see and tend to believe the computer's decision before making a judgement (Danelid, 2024). This bias is also related to the concept of complacency in automated systems. Complacency in automation systems refers to the situation where individuals working with computerised systems overly trust automation and do not make necessary controls and assume that everything is in line (Parasuraman & Manzey, 2010). Thus, users tend to find automation systems more reliable and accurate in a biased way.

Automation bias has been seen in many areas, including healthcare, education, the public sector and government (Goddart et al., 2012). For example, previous studies of cockpit crews have shown that automation bias manifests itself in the form of errors of omission and errors of application. (Vered et al., 2023). Another study examined the impact of automated diagnostic systems in healthcare on cardiologists' ECG interpretations. The study found that these systems reduced the rate of correct diagnoses by experts and reduced their confidence in their decisions. (Bond et al., 2023). The most important feature of AI-supported applications in marketing is market segmentation and personalization. (Mirwan, 2023). While AI can help marketers and consumers make decisions to design effective campaigns, these automated systems, especially decision-making systems, can cause automation bias because consumers or marketers tend to directly accept decisions or suggestions made by automated systems (e.g. Goddard et al., 2012; Kulpfer et al., 2023).

In summary, automation bias is the overconfidence in many automation systems described in the previous section. This trust stems from the bias of the users, even if the decisions are wrong. Psychologists have explained this concept with concepts such as social loafing, cognitive laziness, and the tendency to obey authority. Two types of errors occur in this context. The first is that experts or decision makers (e.g. consumers, developers) ignore the incorrect operation of automated systems. The second is that decision makers recognise the errors of automation systems but still trust the decisions of automation systems, even if they are supported by different information.

2.2. Algorithmic Bias

Artificial Intelligence has become increasingly popular as a tool for increasing efficiency by automating business processes. However, many researchers and practitioners have also raised concerns about the fairness and bias of AI (Wang, Harper, & Zhu, 2020; Panch et al., 2019). Specifically, algorithmic bias causes AI to systematically advantage or disadvantage one group. (Sen et al., 2020). This has been a major concern in the decision-making processes and marketing activities of machine learning-based algorithms (Akter et al., 2022). These biases have led to inequality, unfair results and discrimination in some cases, questioning the trust in AI (Shin & Shin, 2023).

Various studies have been conducted on the causes of algorithmic biases affecting consumers and users. These can be caused by unrepresentative datasets, poor models, faulty algorithm designs, and human biases when designing marketing models (Akter et al., 2022). These biases have manifested themselves in different cases with negative consequences in the gender, racial and socio-economic status (Akter et al., 2021a). For example, Amazon's AI-powered facial recognition system 'Rekognition' performed worse in identifying the gender of dark-skinned individuals and women (Singer, 2018; Wen & Holweg, 2024). Similarly, in 2016, Google established an AI-supported tracking system to monitor and prevent hate speech on websites and social media platforms. However, this system incorrectly labelled tweets by African Americans as hate speech (Martin, 2019). Another case involves the algorithms used in Google ads, which have resulted in women being less likely to be shown high-paying jobs (Patel, 2019). A notable case of the effects of algorithmic biases in the business world was experienced at Amazon. In 2014, Amazon implemented an AI-enabled technology system for recruitment decisions and CV screening processes over one year. After one year, it was found that this system was trained with biased historical data, which gave advantages to male candidates and discriminated against women (Dastin, 2018).

Although algorithmic bias is a common term, some researchers have argued that the cause of algorithmic biases is that the data used to train the AI systems are themselves biased (Gupta & Krishnan, 2020). Similarly, another study has shown that the source of algorithmic bias is methodological and social bias in the data sets. In particular, algorithms may lead to bias when these data sets are not representative of the target population, when the size of the data sets is small, or when factors such as selection bias and outgroup homogeneity come into play (Akter et al., 2021b). For example, according to Weissman (2018), the AI-based system used by Amazon for recruitment was discontinued because it was biased against women. They found that the source of the bias was that the data sets they used were mostly for men. Akter et al. (2021b) also mentioned different issues of algorithmic biases. These include the small size of data sets, the popularity of some items over others, and the blind spots that recommendation algorithms create for users. In addition, these algorithms cause significant limitations in the user experience by making it difficult to discover certain products.

Another algorithmic bias is methodological bias. In particular, correlation bias, overgeneralisation of findings, and confirmation bias, where individuals prefer information that conforms to their beliefs, can methodologically cause machine learning to produce incorrect results (Thiem et al., 2020). In addition, another source of algorithmic prejudice is socio-cultural factors. Socio-demographic characteristics that already exist in society may increase algorithmic judgements and cause discrimination against disadvantaged groups based on factors such as religion, gender, ethnicity, etc. (Akter et al., 2021b). For example, it was noted that some of Facebook's adverts, such as for credit, employment and housing, could not be viewed by certain groups of African origin (Angwin et al., 2017). Similarly, people of black ethnicity were more likely to encounter biased results related to crime in Google searches (Kasperkevic, 2015). Some cases of algorithmic errors include Facebook's ads showing gender bias (Lambrecht and Tucker, 2018), Orbitz offering more expensive travel services to Mac users than Windows users (BBC, 2012) and Uber and Lyft showing higher prices in areas where African Americans live (Akter et al., 2022).

In this context, with the development of machine learning and AI, marketers have made strategic decisions in their respective markets by creating data sets related to users' behaviour and personality traits. However, despite this development, biases in the datasets have caused unequal, unfair, and unjust effects among users. While there are theoretically studies that explain this issue, there are still insufficient studies in industrial or other applied fields (Akter et al., 2023).

3. Algorithmic Errors and Strategies to Enhance Consumer Satisfaction

3.1. Algorithmic Errors and Consumer Satisfaction

Although AI services are transforming business and society, failures have been seen in some scenarios due to algorithmic errors (Griffith, 2017). For example, Tesla's autopilot accidents, bad news suggested in Facebook's year-end recommendation photos and videos, Microsoft's racist Thai AI, Amazon's sending wrong e-mails are some of these errors. In addition, consumers are further frustrated by the uncertainty of why algorithmic errors are caused and not knowing how to interpret them (Puntoni et al., 2021).

When consumer reactions are analysed in AI-supported services, one of the main problems is the loss of consumer trust. When the literature is investigated, if the individual does not have information about the performance of the algorithm or the human (service provider), they lose trust in both in a similar way. However, when consumers compare the recommendations of algorithms with human-assisted services, they are more likely to distrust algorithms than human-assisted services when they observe an error or a bad recommendation in the algorithms (Dietvorst, Simmons, and Massey 2015; Longoni et al., 2023). In other words, people are less tolerant of errors in algorithms, although they recognise that both algorithms and humans can make mistakes (Dietvorst et al., 2015).

When consumers' expectations are not met or when they receive a failed service, AI failures can often evoke negative emotions in consumers rather than positive reactions. When a chatbot does not understand the customer's problem, gives irrelevant answers or demands excessive information, frustration, anger, feeling cheated and passive defeat are the most common reactions among customers (Castillo et al., 2021; Zhang et al., 2024). As a result of a study, when consumers interact with the chatbot in anger, it negatively affects consumer satisfaction, firm evaluation and purchase behaviour (Crolic et al., 2022). In general, when a service experience is perceived as a positive, consumers interact positively with service providers. Whereas, AI tools such as chatbots do not meet consumers' expectations service failures occur (Gelbrich, 2010). This situation leads to users feeling angry, frustrated and helpless. This can lead to word-of-mouth marketing, complaints and customer revenge (Zhang et al., 2024).

There are various studies examining the impact of chatbots on customer satisfaction (Castillo et al., 2021; Eren, 2021; Kvale et al., 2020). A qualitative study with twenty-seven customers revealed five different reasons for unsuccessful interactions between consumers and chatbots. These issues are difficulties with authenticity, cognitive, emotional, functionality and integration. (Castillo et al., 2021). When looking at detail of study, it was found that customers pay attention to cues such as language structure, repetitive responses and speed of response to understand whether they are talking to a chatbot or a human (authenticity). In addition, disruption of the chat flow and misinterpretations by the chatbot are among the cognitive challenges. Lack of empathy, lack of personalisation, insufficient effort and forced interaction were considered as emotional problems. Other major challenges are integration problems, such as narrow response and limited options (functionality), lack of human support and disconnected coordination processes. In summary, chatbots experience different difficulties related to customer experience, and these problems increase the negative experience.

Unlike human errors, consumers can generally generalise AI errors. This is because consumers can attribute all errors that occur in an AI system to the AI systems. Users tend to generalise AI errors more widely than human errors. In the literature, this effect is described as algorithmic transfer (Longoni et al., 2023). In general, people perceive AI systems as a homogeneous group separate from themselves, whereas they perceive themselves as more heterogeneous and different (Longoni et al., 2023). Therefore, consumers may generalise the algorithm errors of one AI system to all other intelligent systems. These generalisations negatively affect consumer satisfaction (Chen, 2024; Langoni et al., 2023) and their willingness to use AI services also decreases (Castillo et al., 2021). Generalising AI errors and not compensating for these errors further increases the customer's negative experience and reduces the willingness to use AI systems (Mahmood et al., 2022).

In addition, the algorithms used by brands do not always perform as expected, and in some cases even damage the brand (Srinivasan & Sarial, 2021). In marketing, algorithm errors can negatively impact the consumer experience or damage consumer expectations of brands. In a survey conducted by the CMO Council and Dow Jones Inc, 78 per cent of chief marketing officers expressed concern about algorithm errors damaging their brands (Vizard, 2017). Thus, although AI systems offer innovations and conveniences that improve the consumer experience, AI failures also cause significant mistrust. Users tend to generalise the failure of an algorithm to all AI technologies. Therefore, it is important for brands offering AI-based services to be transparent about algorithms and to offer solutions without completely excluding human support. Otherwise, the anger, disappointment and loss of trust that arise when consumers' expectations are not met can damage brand reputation and endanger future business opportunities.

3.2. Suggestions for Improving Customer Experience in Automation Technologies

Nowadays, organisations are using AI-enabled systems to improve consumer satisfaction and achieve organisational agility. However, technological systems sometimes fail to fully meet human expectations. Especially in emotional and complex tasks, the performance of AI tools is highly questioned and reactions to algorithmic errors can have serious consequences. In this section, how consumers perceive the A tools and under which conditions errors can be minimised will be discussed.

Various suggestions have been made for consumers to compensate for AI errors and prevent their negative effects on brands. After AI performs a task, consumers might react less negatively to the errors caused by the algorithms if the logic or process behind the algorithm is comprehensible. When consumers can interpret the algorithm, their reactions become even less negative. This strategy seems more effective during subjective task phases (Chen, 2024). Another strategy is to acknowledge mistakes and responsibility, followed by a sincere apology to make amends for AI mistakes. In a study by Mahmood et al. (2022), an AI agent that admits responsibility and sincerely apologizes is perceived to be more intelligent and sympathetic and effective in recovering from mistakes. Therefore, a well-designed apology method can be a part of an effective strategy for managing the mistakes of AI agents. However, it should be noted that a poorly designed apology can sometimes have a more negative impact than no apology at all. In a study with voice assistants, participants were less willing to use the AI tool if the AI tool blamed someone else when apologizing, compared to not apologizing at all (Mahmood et al., 2022).

For emotional and sensitive interactions or more complex tasks, a hybrid approach is proposed, where both AI tools and human intelligence can be utilized. This approach will help achieve a balance between consumer satisfaction and effectiveness (Mikalef et al., 2021). While AI tools can effectively be used for more routine tasks, it may seem difficult in some circumstances to replace a human being completely. Therefore, cooperation between AI tools and human co-operation in inter-organisational marketing processes is recommended (Mikalef et al., 2021). Users and developers sometimes overly rely on AI-supported automation systems even though these systems can make incorrect judgments. However, AI tools may still have problems understanding humans and identifying their needs accurately. Therefore, it is recommended that both chatbots and humans are utilized in online retail transactions to ensure effective human-machine interaction (Chen et al., 2021).

As a different approach, it is suggested that service providers should clearly state the limitations of AI to customers. This approach can help manage customers' negative reactions and expectations when AI cannot cope with complex tasks. Kaplan & Haenlein (2019) suggest clearly explaining and making AI applications understandable to increase customer experience and trust towards AI applications. The Singapore Personal Data Protection Commission (2018) also recommends that AI applications should be transparent, fair and their mechanisms clearly disclosed.

Making AI decision-making processes more transparent and understandable can increase customer trust and acceptance (Akter et al., 2021; Volkmar et al., 2022). In addition, informing or educating customers and managers about AI capabilities and limitations can create a more realistic expectation of AI performance. Given that managers and customers are less tolerant of AI errors than human errors (Dietvorst et al., 2015; Volkmar et al., 2022), some competencies can be provided to organisations to increase the AI literacy of managers and users (Long & Magerko, 2020).

As a result, when we consider the above studies, no matter how advanced the AI used, the user trust and satisfaction will largely depend on the user's understanding of the AI systems. To establish healthier and more trust-based relationships with users, it would be a better approach to be transparent and take responsibility for mistakes rather than hiding mistakes. The basis of the success of sustainable AI technologies lies in their human-centred design, rather than technical perfection.

4. Conclusion

The use of automation technologies to enhance customer experience and significantly improve business processes is prevalent. However, although these technologies have an advanced perspective, they carry some risks and bias that users ignore. Therefore, this situation can also damage the consumer's trust. Although AI-supported automation solutions such as chatbots, recommendation systems, automated e-mail services increase customer satisfaction, algorithmic errors and automation bias negatively affect customer satisfaction rather than increasing it.

In this study, the deceptive effects of automation and algorithmic bias on consumers are analysed. While automation bias means individuals' overconfidence in automated systems even though they are wrong, algorithmic bias is the unfair results in certain groups due to biases in data sets or for different reasons. This situation causes greater ethical problems, especially in areas such as recruitment, credit rating evaluation, and advertising. For example, in a recruitment application, AI-supported systems may cause discrimination against certain groups by only looking at historical data. Similarly, consumer experience, companies' reputation and brand credibility are greatly affected by errors caused by algorithms.

Different strategies have been proposed to increase the efficiency of automation technologies and positively influence the consumer experience. These include making AI-supported automation systems more transparent, taking responsibility for errors, ensuring that human-assisted services are not completely disabled. Furthermore, increasing the AI knowledge and skills of consumers and managers will enable more informed and ethical use. For AI-supported automation system developers' algorithms to provide more impartial and fair solutions, increasing the variety of data sets and having audits will increase reliability. In addition, not completely disabling the human factor in AI-supported services plays a critical role in increasing consumer satisfaction.

In this context, although automation technologies create great possibilities in customer experience in the field of marketing, ethical and correct use of these technologies needs to be considered. A human-centred fair AI approach can create a more sustainable, reliable and digital ecosystem. To make the most of AI and automation technologies, both developers and users should not ignore the risks and limitations of these systems. Optimising the advantages of technological systems with ethical, fair practices is essential for a sustainable digital future.

5. Declaration of Interest

"No conflicts of interest exist."

6. Declaration of generative AI and AI-assisted technologies in the writing process

"During the preparation of this work the author(s) used ChatGPT 4o to improve language and readability with caution. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication."

References

Abrokwah-Larbi, K., & Awuku-Larbi, Y. (2024). The impact of artificial intelligence in marketing on the performance of business organizations: Evidence from SMEs in an emerging economy. *Journal of Entrepreneurship in Emerging Economies, 16*(4), 1090–1117.

Adamopoulou, E., & Moussiades, L. (2020). Chatbots: History, technology, and applications. *Machine Learning with Applications, 2*, Article

Aguirre, S., & Rodriguez, A. (2017). Automation of a business process using robotic process automation (RPA): A case study. In *Applied Computer Sciences in Engineering: 4th Workshop on Engineering Applications, WEA 2017, Cartagena, Colombia, September 27-29, 2017, Proceedings 4* (pp. 65–71). Springer International Publishing.

Akter, S., Dwivedi, Y. K., Biswas, K., Michael, K., Bandara, R. J., & Sajib, S. (2021a). Addressing algorithmic bias in AI-driven customer management. *Journal of Global Information Management, 29*(6), 1–27.

Akter, S., Dwivedi, Y. K., Sajib, S., Biswas, K., Bandara, R. J., & Michael, K. (2022). Algorithmic bias in machine learning-based marketing models. Journal of Business Research, 144, 201–216.

Akter, S., McCarthy, G., Sajib, S., Michael, K., Dwivedi, Y. K., D'Ambra, J., & Shen, K. N. (2021b). Algorithmic bias in data-driven innovation in the age of AI. International Journal of Information Management, 60, 102387.

Akter, S., Sultana, S., Mariani, M., Wamba, S. F., Spanaki, K., & Dwivedi, Y. K. (2023). Advancing algorithmic bias management capabilities in AI-driven marketing analytics research. Industrial Marketing Management, 114, 243–261.

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., ... & Yang, H. (2018). Consumer choice and autonomy in the age of artificial intelligence and big data. Customer Needs and Solutions, 5, 28–37.

Angwin, J., Tobin, A., & Varner, M. (2017). Facebook (still) letting housing advertisers exclude users by race. ProPublica. https://www.propublica.org/article/facebook-advertising-discrimination-housing-race-sex-national-origin.

BBC News. (2012, June 26). Travel site Orbitz offers Mac users more costly hotels. BBC News. https://www.bbc.com/news/technology-18595347

Berger, B., Adam, M., Rühr, A., & Benlian, A. (2021). Watch me improve—Algorithm aversion and demonstrating the ability to learn. Business & Information Systems Engineering, 63(1), 55–68.

Bond, R. R., Novotny, T., Andrsova, I., Koc, L., Sisakova, M., Finlay, D., ... & Malik, M. (2018). Automation bias in medicine: The influence of automated diagnoses on interpreter accuracy and uncertainty when reading electrocardiograms. Journal of Electrocardiology, 51(6), S6–S11.

Boomerang. (n.d.). Boomerang for Gmail homepage. Retrieved December 10, 2024, from https://www.boomeranggmail.com

Castillo, D., Canhoto, A. I., & Said, E. (2021). The dark side of AI-powered service interactions: Exploring the process of co-destruction from the customer perspective. The Service Industries Journal, 41(13–14), 900–925.

Chen, C. (2024). How consumers respond to service failures caused by algorithmic mistakes: The role of algorithmic interpretability. Journal of Business Research, 176, 114610.

Chen, J. S., Tran-Thien-Y, L., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. International Journal of Retail & Distribution Management, 49(11), 1512–1531.

Crolic, C., Thomaz, F., Hadi, R., & Stephen, A. T. (2022). Blame the bot: Anthropomorphism and anger in customer–chatbot interactions. Journal of Marketing, 86(1), 132– 148.

Daase, C., Staegemann, D., Volk, M., Nahhas, A., & Turowski, K. (2020). Automation of customer-initiated back-office processes: A design science research approach to link robotic process automation and chatbots. [Journal Name if available], [Volume if available], [Page numbers if available].

Danelid, F. (2024). *Automation bias in public sector decision-making: A systematic review* (Master's thesis). [Umeå University]

Dastin, J. (2018, [Month Day]). Amazon scraps secret AI recruiting tool that showed bias against women. *Reuters*. https://www.reuters.com/article

Ducheneaut, N., & Bellotti, V. (2001). E-mail as habitat: An exploration of embedded personal information management. Interactions, 8(5), 30–38.

Eren, B. A. (2021). Determinants of customer satisfaction in chatbot use: evidence from a banking application in Turkey. *International Journal of Bank Marketing*, *39*(2), 294- 311.

Farbod, S. (2024). *Exploring the dark side of AI-enabled services: Impacts on customer experience and well-being* [Manuscript in preparation].

Gavrila Gavrila, S., Blanco González-Tejero, C., Gómez Gandía, J. A., & de Lucas Ancillo, A. (2023). The impact of automation and optimization on customer experience: A consumer perspective. Humanities and Social Sciences Communications, 10(1), 1– 10.

Ghalme, S., Shelke, K., Kadam, R., & Tupe, U. (2023, June). Automated emails and data segregation using Python. In 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS) (pp. 1701–1705). IEEE.

Goddard, K., Roudsari, A., & Wyatt, J. C. (2012). Automation bias: A systematic review of frequency, effect mediators, and mitigators. Journal of the American Medical Informatics Association, 19(1), 121–127.

Goldberg, K. (2011). What is automation? IEEE Transactions on Automation Science and Engineering, 9(1), 1–2.

Grevet, C., Choi, D., Kumar, D., & Gilbert, E. (2014, April). Overload is overloaded: Email in the age of Gmail. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (pp. 793–802).

Griffith, E. (2017, September 23). 10 embarrassing algorithm fails. PCMag. https://www.pcmag.com/feature/356387/10-embarrassing-algorithm-fails

Groover, M. P. (2016). Automation, production systems, and computer-integrated manufacturing (4th ed.). Pearson Education India.

Gupta, D., & Krishnan, T. S. (2020). Algorithmic bias: Why bother. California Management Review, 63(3), 1–7.

Hagen, L., Uetake, K., Yang, N., Bollinger, B., Chaney, A. J., Dzyabura, D., & Zhu, Y. (2020). How can machine learning aid behavioral marketing research? Marketing Letters, 31, 361–370.

He, X., Liao, L., Zhang, H., Nie, L., Hu, X., & Chua, T. S. (2017, April). Neural collaborative filtering. In *Proceedings of the 26th international conference on world wide web* (pp. 173-182).

Hitomi, K. (1994). Automation—Its concept and a short history. Technovation, 14(2), 121–128.

Huseynov, F. (2023). Chatbots in digital marketing: Enhanced customer experience and reduced customer service costs. In Contemporary approaches of digital marketing and the role of machine intelligence (pp. 46–72). IGI Global.

Janssen, C. P., Donker, S. F., Brumby, D. P., & Kun, A. L. (2019). History and future of human- automation interaction. International Journal of Human-Computer Studies, 131, 99– 107.

Kaczorowska-Spychalska, D. (2019). How chatbots influence marketing. *Management, 23*(1), [251-268]. https://doi.org/10.2478/manment-2019-0015

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62(1), 15–25.

Karami, A., Shemshaki, M., & Ghazanfar, M. (2024). Exploring the ethical implications of AI-powered personalization in digital marketing. Data Intelligence. Advance online publication.

Karau, S. J., & Williams, K. D. (1993). Social loafing: A meta-analytic review and theoretical integration. Journal of Personality and Social Psychology, 65(4), 681–706.

Kasperkevic, J. (2015, July 2). Google says sorry for racist auto-tag in photo app. The Guardian. https://www.theguardian.com/technology/2015/jul/01/google-sorry-racist- auto-tag-photo-app

Kokkinou, A., & Cranage, D. A. (2013). Using self-service technology to reduce customer waiting times. International Journal of Hospitality Management, 33, 435– 445.

König, M., Bein, L., Nikaj, A., & Weske, M. (2020). Integrating robotic process automation into business process management. In Business Process Management: Blockchain and Robotic Process Automation Forum: BPM 2020 Blockchain and RPA Forum, Seville, Spain, September 13–18, 2020, Proceedings 18 (pp. 132–146). Springer International Publishing.

Kupfer, C., Prassl, R., Fleiß, J., Malin, C., Thalmann, S., & Kubicek, B. (2023). Check the box! How to deal with automation bias in AI-based personnel selection. Frontiers in Psychology, 14, 1118723.

Kushmerick, N., & Lau, T. (2005, January). Automated email activity management: An unsupervised learning approach. In Proceedings of the 10th International Conference on Intelligent User Interfaces (pp. 67–74).

Kvale, K., Freddi, E., Hodnebrog, S., Sell, O. A., & Følstad, A. (2020, November). Understanding the user experience of customer service chatbots: what can we learn from customer satisfaction surveys?. In *International Workshop on Chatbot Research and Design* (pp. 205-218). Cham: Springer International Publishing.

Lakshmi, N. D. R. T. V., Yadav, N. L. S., & Reddy, N. M. A. (2024). Robotic process automation in banking for better customer experience. *Deleted Journal*, *2*(07), 2027–2029. https://doi.org/10.47392/irjaeh.2024.0276

Lepri, B., Oliver, N., Letouzé, E., Pentland, A., & Vinck, P. (2018). Fair, transparent, and accountable algorithmic decision-making processes: The premise, the proposed solutions, and the open challenges. Philosophy & Technology, 31(4), 611– 627.

Longoni, C., Cian, L., & Kyung, E. J. (2023). Algorithmic transference: People overgeneralize failures of AI in the government. Journal of Marketing Research, 60(1), 170–188.

Madakam, S., Holmukhe, R. M., & Jaiswal, D. K. (2019). The future digital workforce: Robotic process automation (RPA). JISTEM-Journal of Information Systems and Technology Management, 16, e201916001.

Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T., ... & Söllner, M. (2019). AI-based digital assistants: Opportunities, threats, and research perspectives. *Business & Information Systems Engineering*, *61*, 535-544.

Mahmood, A., Fung, J. W., Won, I., & Huang, C. M. (2022, April). Owning mistakes sincerely: Strategies for mitigating AI errors. In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (pp. 1–11).

Mane, S., & Rayappa, B. V. (2022). Customized Automated Email Bot. *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*, 10(1), 1656-1658. https://doi.org/10.22214/ijraset.2022.40083

Mehrotra, S., Degachi, C., Vereschak, O., Jonker, C. M., & Tielman, M. L. (2023). A systematic review on fostering appropriate trust in human-AI interaction. arXiv Preprint, arXiv:2311.06305. https://arxiv.org/abs/2311.06305

Mikalef, P., Conboy, K., & Krogstie, J. (2021). Artificial intelligence as an enabler of B2B marketing: A dynamic capabilities micro-foundations approach. Industrial Marketing Management, 98, 80–92.

Mirwan, S. H. (2023). Using artificial intelligence (AI) in developing marketing strategies. International Journal of Applied Research and Sustainable Sciences (IJARSS), 1, 225–238.

Molnár, G., & Szüts, Z. (2018, September). The role of chatbots in formal education. In 2018 IEEE 16th International Symposium on Intelligent Systems and Informatics (SISY) (pp. 000197–000202). IEEE.

Mosier, K. L., & Skitka, L. J. (2018). Human decision makers and automated decision aids: Made for each other? In Automation and human performance (pp. 201–220). CRC Press.

Palanque, P., Campos, P. F., Nocera, J. A., Clemmensen, T., & Roto, V. (2019). User experience in an automated world. In Human-Computer Interaction–INTERACT 2019: 17th IFIP TC 13 International Conference, Paphos, Cyprus, September 2–6, 2019, Proceedings, Part IV (pp. 706–710). Springer International Publishing.

Panch, T., Mattie, H., & Atun, R. (2019). Artificial intelligence and algorithmic bias: implications for health systems. *Journal of global health*, *9*(2), 020318.

Parasuraman, R., & Manzey, D. H. (2010). Complacency and bias in human use of automation: An attentional integration. Human Factors, 52(3), 381–410.

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. Human Factors, 39(2), 230–253.

Park, S., Zhang, A. X., Murray, L. S., & Karger, D. R. (2019, May). Opportunities for automating email processing: A need-finding study. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (pp. 1– 12).

Patel, P. (2019, April 25). Women less likely to be shown ads for high-paying jobs. IEEE Spectrum. https://spectrum.ieee.org/women-less-likely-to-be-shown-ads-for- highpaying-jobs

Personal Data Protection Commission Singapore. (2018). Discussion paper on artificial intelligence (AI) and personal data – Fostering responsible development and adoption of AI. https://www.pdpc.gov.sg

Pricilla, C., Lestari, D. P., & Dharma, D. (2018, August). Designing interaction for chatbot-based conversational commerce with user-centered design. In 2018 5th International Conference on Advanced Informatics: Concept Theory and Applications (ICAICTA) (pp. 244–249). IEEE.

Rae, T. (2016). The effect of marketing automation on customer experience (Bachelor's thesis). [Aalto University],

Ribeiro, J., Lima, R., Eckhardt, T., & Paiva, S. (2021). Robotic process automation and artificial intelligence in Industry 4.0–A literature review. Procedia Computer Science, 181, 51–58.

Sen, S., Dasgupta, D., & Gupta, K. D. (2020, July). An empirical study on algorithmic bias. In 2020 IEEE 44th Annual Computers, Software, and Applications Conference (COMPSAC) (pp. 1189–1194). IEEE.

Shi, Y., Larson, M., & Hanjalic, A. (2014). Collaborative filtering beyond the user-item matrix: A survey of the state of the art and future challenges. *ACM Computing Surveys (CSUR)*, *47*(1), 1-45.

Shin, D., & Shin, E. Y. (2023). Data's impact on algorithmic bias. Computer, 56(6), 90–94.

Singer, N. (2018, July 24). Amazon is pushing facial technology that a study says could be biased. The New York Times. https://www.nytimes.com/[full-article-link-if-available]

Singh, S., & Namekar, S. (2020). A review on automation of industries. International Journal of Engineering Applied Sciences and Technology, 4(12), 298–300.

Skitka, L. J., Mosier, K. L., Burdick, M., & Rosenblatt, B. (2000). Automation bias and errors: Are crews better than individuals? The International Journal of Aviation Psychology, 10(1), 85–97.

Srinivasan, R., & Sarial-Abi, G. (2021). When algorithms fail: Consumers' responses to brand harm crises caused by algorithm errors. Journal of Marketing, 85(5), 74–91.

Su, X., & Khoshgoftaar, T. M. (2009). A survey of collaborative filtering techniques. *Advances in artificial intelligence*, *2009*(1), 421425.

Thiem, A., Mkrtchyan, L., Haesebrouck, T., & Sanchez, D. (2020). Algorithmic bias in social research: A meta-analysis. PLOS ONE, 15(6), e0233625.

Van Esch, P., & Stewart Black, J. (2021). Artificial intelligence (AI): Revolutionizing digital marketing. Australasian Marketing Journal, 29(3), 199–203.

Vaughan, P. (2012, September 26). Email marketing automation: Examples and strategies. HubSpot Blog. Updated April 18, 2023. https://blog.hubspot.com/marketing/email-marketing-automation-examples#what-is-email-marketing-auto

Vered, M., Livni, T., Howe, P. D. L., Miller, T., & Sonenberg, L. (2023). The effects of explanations on automation bias. Artificial Intelligence, 322, 103952.

Vizard, S. (2017, December 30). The brand safety fallout: Three in four marketers say brand reputation has taken a hit. Marketing Week. https://www.marketingweek.com/2017/09/26/brand-safety-fallout/

Volkmar, G., Fischer, P. M., & Reinecke, S. (2022). Artificial intelligence and machine learning: Exploring drivers, barriers, and future developments in marketing management. Journal of Business Research, 149, 599–614.

Weissman, C. G. (2018, October 10). Amazon created a hiring tool using A.I. It immediately started discriminating against women. Slate. https://slate.com/business/2018/10/amazon-artificial-intelligence-hiring- discrimination-women.html

Wen, Y., & Holweg, M. (2024). A phenomenological perspective on AI ethical failures: The case of facial recognition technology. AI & Society, 39(4), 1929– 1946.

Wertenbroch, K. (2019). From the editor: A manifesto for research on automation in marketing and consumer behavior. Journal of Marketing Behavior, 4(1), 1–10.

Xu, Y., Shieh, C. H., van Esch, P., & Ling, I. L. (2020). AI customer service: Task complexity, problem-solving ability, and usage intention. Australasian Marketing Journal, 28(4), 189–199.

Yang, B., Han, C., Li, Y., Zuo, L., & Yu, Z. (2021). Improving conversational recommendation systems' quality with context-aware item meta information. arXiv Preprint, arXiv:2112.08140. https://arxiv.org/abs/2112.08140

Yıldıran, Y. D., & Erdem, Ş. (2024). Yapay zeka tabanlı chatbot hizmetinin kullanıcı alışkanlık ve davranışları üzerine etkileri ve bir uygulama. Marmara Üniversitesi İktisadi ve İdari Bilimler Dergisi, 46(1), [page numbers if available].

Zhang, R. W., Liang, X., & Wu, S. H. (2024). When chatbots fail: Exploring user coping following a chatbot-induced service failure. Information Technology & People, 37(8), 175–195.

Zhou, J., Wang, B., He, R., & Hou, Y. (2021, November). CRFR: Improving conversational recommender systems via flexible fragments reasoning on knowledge graphs. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing (pp. 4324–4334).

Chapter 7

AI, Addiction, and Consumer Well-Being

Dicle Yurdakul[1]

Abstract

The increasing integration of Artificial Intelligence (AI) in marketing has transformed consumer engagement, enabling hyper-personalization and predictive analytics. While AI-driven marketing enhances efficiency and user experience, it also raises ethical concerns regarding consumer autonomy, addiction and manipulation. This chapter explores the ethical implications of AI in marketing, emphasizing the role of AI in shaping consumer behaviors through personalized content, algorithmic decision-making and targeted advertisements. It discusses the neurological and psychological mechanisms underlying consumer addiction, the cognitive and emotional effects of AI-driven marketing and the broader social and economic consequences.

To address these concerns, the chapter proposes solutions in three key areas: corporate responsibility, consumer awareness and policy-level interventions. Ethical AI marketing requires companies to adopt transparent algorithms, mitigate biases and implement responsible data practices. Empowering consumers through digital literacy initiatives and promoting digital well-being strategies can enhance their ability to navigate AI-driven content critically. Additionally, regulatory frameworks and industry-wide best practices are necessary to establish accountability, ensure fair marketing practices and protect consumer rights.

By fostering an ethical approach to AI in marketing, stakeholders can balance innovation with consumer well-being, creating a sustainable and equitable digital marketplace. This chapter highlights the need for collaborative efforts among businesses, policymakers and researchers to ensure that AI technologies promote ethical consumer interactions while mitigating potential harms.

1 Doç. Dr., Altınbaş Üniversitesi, dicle.yurdakul@altinbas.edu.tr,
ORCID ID 0000-0001-9026- 8606

https://doi.org/10.58830/ozgur.pub710.c3024

1. Introduction

Artificial Intelligence (AI) has significantly transformed the marketing landscape, enabling businesses to deliver unparalleled levels of personalization and efficiency. Through advanced data analytics and machine learning algorithms, AI allows companies to understand consumer behavior more accurately and engage with their audiences in highly targeted ways. However despite its benefits, AI-driven marketing raises significant concerns regarding consumer addiction and ethical implications. As AI systems become more sophisticated in predicting and influencing human behavior, questions arise about the extent to which they manipulate consumer choices and foster unhealthy consumption habits. This chapter explores the increasing influence of AI-driven marketing on consumer addiction within digital contexts, and examines the ethical considerations surrounding AI's role in shaping consumer behavior.

1.1. Overview of AI-driven marketing and its increasing influence

AI-driven marketing leverages machine learning algorithms and data analytics to tailor strategies to individual consumer preferences, enhancing both user experience and engagement. Unlike traditional marketing approaches that rely on broad demographic categories, AI enables hyper-personalization by analyzing vast amounts of consumer data in real time. This capability allows marketers to anticipate consumer needs and deliver personalized content, thereby increasing conversion rates and fostering long-term customer relationships.

One of the key advantages of AI in marketing is its ability to optimize decision-making. AI systems can process immense amounts of data which allows marketers to adjust campaigns dynamically based on consumer responses (Bhargava & Velasquez, 2020). This agility enhances marketing effectiveness by ensuring that campaigns remain relevant and adaptive to shifting consumer trends. Moreover, AI-powered automation streamlines marketing processes, reducing operational costs while improving efficiency.

AI also plays a crucial role in predictive analytics to forecast purchasing behaviors and tailor marketing strategies accordingly. By identifying patterns in consumer behavior AI can determine which products or services are most likely to appeal to specific audiences, leading to more targeted advertising efforts. This predictive capability not only enhances marketing efficiency but also creates a seamless shopping experience for consumers.

Furthermore, AI has transformed customer interactions through chatbots and virtual assistants. These AI-driven tools reduce the burden on human customer service representatives and improve overall customer satisfaction. AI-powered recommendation engines enhance user engagement by suggesting products or content based on past behavior, further demonstrating AI's growing influence in shaping consumer choices.

On the other hand, the increasing reliance on AI in marketing also raises concerns about its impact on consumer autonomy. While AI enhances marketing precision, it also has the potential to manipulate consumer decision-making by exploiting psychological triggers. This raises ethical questions about whether AI-driven marketing strategies prioritize business profits over consumer well-being. The subsequent sections delve deeper into the concept of consumer addiction in digital marketing and the ethical dilemmas associated with AI's influence.

1.2. Definition of consumer addiction in digital marketing

Consumer addiction in digital marketing refers to compulsive engagement with digital platforms and content, often fueled by AI-driven strategies designed to maximize user attention and interaction. AI algorithms play a crucial role in this phenomenon by curating personalized content that aligns with individual preferences which creates an environment where consumers remain engaged for long periods of time. This is evident in social media where AI continuously analyzes user behavior to deliver tailored content, reinforcing engagement and potential addiction (Bhargava & Velasquez, 2020).

One of the most concerning aspects of AI-driven marketing is its ability to predict and influence consumer behavior. The concept of "predictive buying" exemplifies this, where AI anticipates consumer needs and presents products or services before the consumer actively searches for them (Kumar et al., 2024). While this capability enhances convenience, it also fosters compulsive purchasing behaviors by reducing the level of conscious decision-making involved in the buying process. Consumers may find themselves repeatedly engaging with digital platforms and making impulsive purchase due to the persuasive power of AI-driven recommendations.

The addictive nature of AI-powered marketing strategies is further exacerbated by gamification techniques that encourage repeated engagement. Many digital platforms incorporate reward-based systems, such as personalized notifications, incentives and limited-time offers, all of which leverage psychological principles to sustain user interaction. These strategies create dopamine-driven reward loops that make it increasingly difficult for users to disengage which further contributes to behavioral addiction patterns.

2. The Science of Consumer Addiction

2.1. Neurological and Psychological Mechanisms

Consumer addiction refers to encompassing behaviors such as compulsive shopping, excessive gambling and overindulgence in digital media. As this relatively newer form of addiction has become a significant concern in contemporary society, understanding the neurological and psychological mechanisms underlying these behaviors becomes crucial,

The brain's reward system, and in particular the mesolimbic dopamine pathway, is central to the development of addictive behaviors. This pathway is in the ventral tegmental area (VTA) and projects to the nucleus accumbens (NAcc) which is a region critical for processing reward and reinforcement (Volkow & Morales, 2015). Engaging in rewarding activities such as shopping, gambling or consuming digital content stimulates dopamine release in the NAcc, producing pleasurable sensations and reinforcing the behavior (Kalivas, 2009). Repeated exposure to these stimuli strengthens neural pathways associated with compulsive behavior and leads to sensitization and habit formation (Robinson & Berridge, 1993).

Neuroadaptations in the reward system further contribute to consumer addiction. Studies indicate that prolonged engagement with addictive stimuli leads to an overexpression of ΔFosB, a transcription factor associated with heightened sensitivity to rewards (Nestler, 2014). Increased ΔFosB levels enhance motivation for addictive stimuli while diminishing interest in naturally rewarding activities (Leyton & Vezina, 2013). This phenomenon is particularly relevant in digital media addiction where individuals repeatedly seek out social validation through likes and notifications, mirroring the reinforcement mechanisms observed in substance addiction (Berridge & Robinson, 2016).

Another key neurological factor is the impairment of the prefrontal cortex which is the region that is responsible for decision-making and impulse control. fMRI studies reveal that individuals with compulsive consumption tendencies exhibit decreased activity in the prefrontal cortex which impairs their ability to regulate cravings and resist impulsive behaviors (Goldstein & Volkow, 2011). This dysfunction explains why individuals with shopping addiction or gambling disorders continue engaging in excessive spending despite negative consequences.

Additionally, the role of stress and negative affect in consumer addiction has been well-documented. The amygdala, which is a brain region involved in processing emotions, interacts with the reward system to drive compulsive behaviors in response to stress or anxiety (Koob & Volkow, 2016). This interaction explains why individuals often resort to retail therapy or digital escapism as coping mechanisms for emotional distress. Studies suggest that chronic stress increases susceptibility to addiction by altering dopaminergic transmission which makes individuals more prone to compulsive consumption (Everitt & Robbins, 2016).

Beyond neural mechanisms, psychological factors also play a crucial role in consumer addiction. One of the primary drivers is emotional regulation, where individuals engage in addictive behaviors to cope with stress, anxiety, or depression (Kardefelt-Winther, 2014). For example, shopping addiction is often linked to mood regulation where individuals experience temporary relief from negative emotions through purchasing. However this relief is short-term and leads to a cycle of compulsive spending and subsequent guilt (Dittmar, 2005).

Cognitive biases also contribute to addictive consumer behavior. For example, the illusion of control which is a common bias observed in gambling addiction, leads individuals to believe they can influence outcomes despite random chance (Goodie & Fortune, 2013). Similarly, compulsive shoppers exhibit optimism bias as they overestimate the long-term benefits of purchases while underestimating the negative financial impact (Dittmar, 2005). These cognitive distortions reinforce addictive behaviors by justifying repeated engagement with the addictive stimulus.

Furthermore, personality traits such as impulsivity and sensation-seeking are strong predictors of consumer addiction. Studies indicate that individuals high in impulsivity struggle with delayed gratification and are likely to engage in compulsive consumption (Zuckerman & Kuhlman, 2000). Sensation-seeking people who crave novel and stimulating experiences are particularly susceptible to marketing tactics that exploit their desire for excitement (Leyton & Vezina, 2013). These personality-driven tendencies explain why certain individuals are more vulnerable to compulsive shopping and digital addiction.

Another psychological factor influencing consumer addiction is social influence and peer pressure. Research suggests that social norms and perceived expectations significantly impact consumption behavior (Dittmar, 2005). The rise of influencer culture and targeted digital advertising has worsen this effect, making individuals more likely to engage in excessive consumption to conform to societal trends (Berridge & Robinson, 2016). This phenomenon is particularly evident in social media-driven consumerism where individuals seek validation through material possessions.

3. AI, Personalization, and Addiction Triggers

3.1. Personalized Marketing & Algorithmic Manipulation

The introduction of Artificial Intelligence (AI) has revolutionized personalized marketing by enabling the analysis of vast datasets to tailor content and advertisements to individual preferences. This personalization enhances user engagement and drives consumer behavior. However it also raises concerns about algorithmic manipulation where AI systems exploit cognitive biases to influence consumer decisions, potentially leading to addictive behaviors.

AI-driven personalized marketing leverages machine learning algorithms to predict consumer preferences and deliver targeted content. By analyzing user behavior, purchase history, and online interactions, AI systems can create detailed consumer profiles, which allow marketers to customize advertisements and recommendations (Shin & Park, 2019). This level of personalization can enhance user experience by presenting relevant products or services, thereby increasing the likelihood of engagement and conversion.

However the same algorithms that facilitate personalization can also be used to manipulate consumer behavior. Algorithmic manipulation involves designing AI systems to exploit cognitive biases and psychological vulnerabilities. This may lead to nudging consumers toward decisions that may not align with their best interests (Zuboff, 2019). For instance AI can identify users susceptible to impulse buying and strategically present limited-time offers to encourage immediate purchases. This practice raises ethical concerns as it blurs the line between persuasive marketing and exploitation.

Moreover the lack of clarity of many AI algorithms poses challenges in detecting and regulating such manipulative practices. Consumers are often unaware of the extent to which their data is collected and utilized to influence their decisions. This lack of transparency undermines consumer autonomy (Pasquale, 2015). Furthermore the continuous exposure to personalized content may create echo chambers, which in return, contributes to addictive engagement with specific platforms or content types (Pariser, 2011).

3.2. Dark Patterns in Marketing

Dark patterns refer to user interface designs crafted to manipulate users into actions they might not have intended, benefiting the service provider at the user's expense. These deceptive designs exploit human psychology, leading to unintended subscriptions, purchases, or data sharing (Gray et al., 2018). In the context of AI-driven personalization dark patterns can be seamlessly integrated into digital interfaces, making them more effective and harder to detect.

Common examples of dark patterns include disguised advertisements that appear as regular content and misleading opt-out options that make declining services cumbersome (Mathur et al., 2019). When combined with AI these patterns can be personalized based on user behavior. For instance, an AI system might detect a user's hesitation during a purchase and deploy a pop-up offering for a limited-time discount, pressuring the user into completing the transaction.

The integration of dark patterns in AI-driven marketing strategies raises significant ethical and legal issues. Such practices can lead to consumer harm including financial loss and compromised privacy. Moreover they erode trust in digital platforms and can have long-term negative impacts on user well-being (Bösch et al., 2016). Regulatory bodies have begun to take action against the detrimental effects of these dark patterns. For example the European Union's General Data Protection Regulation (GDPR) mandates that consent for data collection "must be freely given, specific, informed and unambiguous". This regulation aims to stop the use of deceptive designs that forces users into data sharing (Utz et al., 2019).

4. Mental Health Implications

As AI-driven consumer experiences become increasingly personalized and engaging, the potential for addiction and its subsequent mental health effects continues to grow. The intersection of technology, marketing strategies, and consumer behavior has led to a landscape where individuals are exposed to persistent stimuli designed to capture attention and influence decisions. While these innovations offer convenience and personalization, they also contribute to cognitive overload, emotional distress and long-term psychological consequences. Understanding these mental health implications is crucial for addressing the risks associated with AI-driven consumerism and formulating interventions that promote healthier engagement.

4.1. Cognitive and Emotional Effects

The psychological impact of consumer addiction extends beyond mere habits as it influences cognitive functions and emotional well-being. One of the primary cognitive effects of excessive consumerism is decision fatigue where individuals become mentally exhausted from the constant bombardment of choices presented through algorithmic recommendations (Baumeister et al., 2008). AI-driven platforms optimize engagement by continuously suggesting products and services tailored to user preferences. However this persistent exposure to choices can damage cognitive processing and reduce individuals' ability to make rational decisions over time (Schwartz, 2004).

Moreover dopaminergic reinforcement mechanisms play a crucial role in the emotional impact of consumer addiction. Research has shown that online shopping and social media engagement stimulate brain's reward system in a manner similar to substance addiction (Montag et al., 2019). The anticipation of a purchase, the act of acquiring a product or receiving positive social feedback (such as likes and comments) triggers dopamine release which may reinforce compulsive engagement. Over time individuals may experience tolerance, where they require more frequent or intense engagement to achieve the same level of satisfaction (Volkow et al., 2016).

Additionally, mood disorders such as anxiety and depression are closely linked to compulsive consumer behaviors. Studies indicate that individuals who engage in excessive shopping or digital consumption often do so as a coping mechanism for stress or negative emotions (Dittmar, 2005). However, rather than alleviating distress, these behaviors often intensify underlying psychological issues. The pleasure derived from consumer-driven activities is frequently followed by post-purchase regret, financial guilt and increased emotional distress (Ridgway et al., 2008). Problematic smartphone use is associated with reduced attention span, memory deficits and difficulty in emotional regulation (Elhai et al., 2017). Excessive engagement with algorithmically curated content on social media platforms leads to a dichotomy between real-life experiences and curated online personas, fostering low self-esteem and social comparison (Vogel et al., 2014). This negative self-perception can contribute to emotional dysregulation and may reinforce cycles of compulsive digital engagement.

4.2. Social and Economic Consequences

Beyond the individual level, the mental health implications of consumer addiction extend to broader societal and economic concerns. One of the most profound social consequences is the erosion of meaningful interpersonal relationships. As individuals become more absorbed in personalized digital experiences, real-life social interactions often diminish, which may lead to increased loneliness and isolation (Twenge et al., 2018). Research has demonstrated that compulsive social media use can lead to withdrawal from face-to-face communication, weakening the quality of personal relationships and reducing overall well-being (Keles et al., 2020).

Financial distress is a direct consequence of compulsive consumer behaviors with significant implications for mental health. AI-driven marketing strategies that exploit impulse-driven purchasing can lead to accumulated debt and chronic stress. Studies have found that individuals struggling with compulsive buying disorder often experience depression and anxiety exacerbated by the overwhelming burden of financial obligations (Müller et al., 2015).

From a broader perspective, the socioeconomic gap exacerbated by AI-driven consumerism is another growing concern. Personalized advertising disproportionately targets low-income consumers who are more susceptible to manipulative marketing tactics and financially risky consumption habits (Newman et al., 2018). This dynamic contributes to a cycle of economic inequality where financially vulnerable individuals are more likely to engage in addictive spending behaviors which further entrenches them in financial instability (Himmelstein et al., 2019).

5. Moving Towards Ethical AI Marketing

The previous discussions have highlighted the profound implications of AI-driven personalization and its potential to manipulate consumer behavior exacerbate mental health issues and widen social and economic inequalities.The addictive nature of personalized marketing, combined with the exploitation of cognitive biases and the proliferation of dark patterns, underscores the urgent need for ethical frameworks to govern the use of AI in marketing. Without intervention, these practices risk deepening consumer harm, eroding trust in digital platforms and perpetuating cycles of inequality. By aligning technological advancements with ethical principles, it is possible to mitigate the negative consequences of AI-driven marketing while fostering a more equitable and sustainable digital ecosystem.

5.1. **Corporate Responsibility & AI Ethics**

The ethical use of AI in marketing begins with corporate accountability. Businesses must adopt practices that prioritize transparency, fairness and consumer well-being over short-term profits. One of the primary ethical concerns in AI marketing is the "black box" nature of algorithms, which poses significant challenges to consumer autonomy. Consumers are often unaware of how their data is used to influence their decisions, undermining their ability to make informed choices (Pasquale, 2015). To address this, companies must adopt transparent AI systems that allow stakeholders to understand how data is collected, processed, and used. Implementing Explainable AI (XAI) tools can help demystify AI-driven decisions, enabling consumers to understand why they are targeted with specific ads or recommendations (Gunning et al., 2019). For example, providing users with clear explanations for personalized content can enhance trust and accountability. Additionally, companies should explicitly inform users when AI is used in marketing campaigns and how their data is being utilized. This can be achieved through transparent privacy policies and user-friendly consent mechanisms (Martin, 2018).

Another critical aspect of corporate responsibility is mitigating bias in AI systems. AI algorithms often bring about biases present in the data used for training, which results to discriminatory outcomes. For instance, certain demographics may be excluded from seeing job ads or offered higher-priced products (Mehrabi et al., 2021). To combat this, companies must ensure that their training data is representative of diverse populations. Regular audits of data sets can identify and correct imbalances, while building diverse teams of data scientists, marketers, and ethicists can help identify potential biases during the development phase (Holstein et al., 2019).

Respecting consumer privacy is another fundamental pillar of ethical AI marketing. Companies must adopt robust measures to protect personal data and prevent misuse. Integrating privacy considerations into the design of AI systems, often referred to as Privacy by Design, ensures that data protection is prioritized from the outset. This includes minimizing data collection, anonymizing data and implementing strong encryption protocols (Cavoukian, 2011). Moreover, marketers should obtain explicit consent from consumers before collecting or using their data. Tools like cookie consent banners and preference centers can empower consumers to control their data, fostering a sense of agency and trust (Acquisti et al., 2015).

Establishing clear accountability frameworks is also essential for ethical AI use. Developing a code of ethics for AI use in marketing provides a clear framework for employees and stakeholders, while regularly monitoring AI systems and publishing transparency reports can demonstrate a commitment to ethical practices (Diakopoulos, 2016).

5.2. Consumer Awareness & Digital Well-being Strategies

Empowering consumers with knowledge and tools to navigate AI-driven marketing is critical for fostering trust and ensuring digital well-being. Many consumers are unaware of how AI is used in marketing or how their data is being utilized, creating a knowledge gap that leaves them vulnerable to manipulation. To bridge this gap, companies and policymakers must invest in consumer education initiatives. Public awareness campaigns can inform consumers about AI's role in marketing, the benefits of personalization, and the risks associated with data misuse (Zuboff, 2019). Additionally, schools, nonprofits and governments can collaborate to teach digital literacy skills, helping consumers understand how to protect their privacy and make informed choices online (Livingstone, 2018).

Giving consumers control over their data and how it is used is another key aspect of ethical AI marketing. Companies should provide tools that allow consumers to manage their data preferences, such as opting out of data collection or deleting their information. Transparency dashboards can show users how their data is being used, enhancing consumer trust and accountability (Binns et al., 2018). By empowering consumers with control, businesses can foster a sense of agency and respect for individual autonomy.

Promoting digital well-being is also essential in the age of AI-driven marketing. The addictive nature of personalized content can lead to overconsumption, addiction, and mental health issues. To address this, marketers should avoid manipulative tactics, such as exploiting cognitive biases or creating addictive content. Instead, they should focus on providing value and fostering positive consumer experiences (Fogg, 2009). Platforms can incorporate features that promote digital well-being, such as screen time limits, reminders to take breaks and tools to reduce exposure to harmful content (Anderson & Jiang, 2018). By prioritizing consumer well-being, businesses can create a healthier and more sustainable digital ecosystem.

Encouraging ethical consumption is another way to drive change. Consumers can support companies that prioritize ethical AI practices, rewarding businesses that align with their values. Advocacy groups can also play a role by raising awareness, organizing campaigns, and holding businesses accountable for unethical practices. By fostering a culture of ethical consumption, it is possible to create a market that rewards responsible behavior and drives positive change.

5.3. **Industry & Policy-Level Solutions for Responsible AI Use**

While individual companies and consumers play a crucial role, systemic change requires collaboration across industries and the implementation of robust policies. Industry associations can develop guidelines and best practices for AI in marketing (IAB, 2020). Introducing certification programs for ethical AI use can incentivize companies to adopt responsible practices, recognizing organizations that prioritize ethical AI (IEEE, 2019).

Governments also have a critical role to play in ensuring the ethical use of AI in marketing through legislation and oversight. For example, The General Data Protection Regulation (GDPR) sets standards for consumer data privacy and consumer rights. Expanding such laws globally can create a more consistent framework for ethical AI use (Voigt & Von dem Bussche, 2017). Additionally, governments should consider enacting laws specifically addressing AI ethics, such as requiring transparency in algorithmic decision-making or prohibiting discriminatory practices (Cath, 2018). By creating a robust regulatory environment, governments can hold businesses accountable and protect consumers from harm.

Collaboration between governments, businesses, and civil society is essential for addressing the complex challenges of AI ethics. These collaborations can facilitate the development of ethical AI frameworks, share best practices, and fund research on AI ethics (Stilgoe et al., 2013). International organizations, such as the United Nations and the World Economic Forum, can also play a role by facilitating global cooperation on AI ethics, ensuring that standards are consistent across borders (Jobin et al., 2019).

Investing in research and innovation is another key strategy for addressing ethical challenges and unlocking the full potential of AI in marketing. Funding research on topics like bias mitigation, explainability and the societal impact of AI can inform best practices and policy decisions (Mittelstadt et al., 2016). Encouraging the development of innovative tools such as privacy-preserving AI techniques (e.g., federated learning) and ethical AI platforms can drive progress in the field (Yang et al., 2019).

The ethical use of AI in marketing is a business necessity. By embracing corporate responsibility, empowering consumers, and advocating for industry-wide solutions, businesses can build trust, foster innovation, and create a more equitable digital landscape. While challenges remain, a collaborative and proactive approach can ensure that AI is used to enhance, rather than exploit, the consumer experience.

References

Acquisti, A., Brandimarte, L., & Loewenstein, G. (2015). Privacy and human behavior in the age of information. Science, 347(6221), 509–514.

Anderson, M., & Jiang, J. (2018). Teens, social media & technology 2018. Pew Research Center. Retrieved from https://www.pewresearch.org

Baumeister, R. F., Vohs, K. D., DeWall, C. N., & Zhang, L. (2007). How emotion shapes behavior: Feedback, anticipation, and reflection, rather than direct causation. Personality and Social Psychology Review, 11(2), 167-203.

Bellamy, R. K. E., Dey, K., Hind, M., Hoffman, S. C., Houde, S., Kannan, K., ... & Zhang, Y. (2018). AI Fairness 360: An extensible toolkit for detecting and mitigating algorithmic bias. IBM Journal of Research and Development, 63(4/5), 4:1–4:15.

Berridge, K. C., & Robinson, T. E. (2016). Liking, wanting, and the incentive-sensitization theory of addiction. American Psychologist, 71(8), 670-679.

Bhargava, V. R., & Velasquez, M. (2020). Ethics of the attention economy: The problem of social media addiction. Business Ethics Quarterly, 30(3), 321-359.

Binns, R., Van Kleek, M., Veale, M., Lyngs, U., Zhao, J., & Shadbolt, N. (2018). Like trainer, like bot? Inheritance of bias in algorithmic content moderation. In Proceedings of the International Conference on Social Informatics (pp. 405–415). Springer.

Bösch, C., Erb, B., Kargl, F., & Kopp, H. (2016). Tales from the dark side: Privacy dark strategies and privacy dark patterns. Proceedings on Privacy Enhancing Technologies, 2016(4), 237-254.

Cath, C. (2018). Governing artificial intelligence: Ethical, legal, and technical opportunities and challenges. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 376(2133).

Cavoukian, A. (2011). Privacy by design: The 7 foundational principles. Information and Privacy Commissioner of Ontario, Canada. Retrieved from https://www.ipc.on.ca

De Pelsmacker, P., Geuens, M., & Van den Bergh, J. (2018). Marketing communications: A European perspective (6th ed.). Pearson Education.

Diakopoulos, N. (2016). Accountability in algorithmic decision making. Communications of the ACM, 59(2), 56–62.

Dittmar, H. (2005). Compulsive buying—a growing concern? An examination of gender, age, and endorsement of materialistic values as predictors. British Journal of Psychology, 96(4), 467-491.

Elhai, J. D., Levine, J. C., Dvorak, R. D., & Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. Journal of Affective Disorders, 207, 251-259.

Everitt, B. J., & Robbins, T. W. (2016). Drug addiction: Updating actions to habits to compulsions ten years on. Annual Review of Psychology, 67, 23-50.

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V. & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. Minds and Machines, 28(4), 689–707.

Fogg, B. J. (2009). A behavior model for persuasive design. In Proceedings of the 4th International Conference on Persuasive Technology (pp. 1–7). ACM.

Goldstein, R. Z., & Volkow, N. D. (2011). Dysfunction of the prefrontal cortex in addiction: Neuroimaging findings and clinical implications. Nature Reviews Neuroscience, 12(11), 652-669.

Gray, K., Kou, Y., Battles, B., Hoggatt, J., & Toombs, A. L. (2018). The dark (patterns) side of UX design. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (pp. 1-14).

Gunning, D., Stefik, M., Choi, J., Miller, T., Stumpf, S., & Yang, G.-Z. (2019). XAI—Explainable artificial intelligence. Science Robotics, 4(37), eaay7120.

Himmelstein, D. U., Lawless, R. M., Thorne, D., Foohey, P., & Woolhandler, S. (2019). Medical bankruptcy: Still common despite the Affordable Care Act. American Journal of Public Health, 109(3), 431-433.

Holstein, K., Vaughan, J. W., Daumé, H., Dudík, M., & Wallach, H. (2019). Improving fairness in machine learning systems: What do industry practitioners need? In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (pp. 1–16). ACM.

IEEE. (2019). Ethically aligned design: A vision for prioritizing human well-being with autonomous and intelligent systems. IEEE Standards Association. Retrieved from https://standards.ieee.org

IAB. (2020). AI in marketing: Best practices and guidelines. Interactive Advertising Bureau. Retrieved from https://www.iab.com

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. Nature Machine Intelligence, 1(9), 389–399.

Kalivas, P. W. (2009). The glutamate homeostasis hypothesis of addiction. Nature Reviews Neuroscience, 10(8), 561-572.

Kardefelt-Winther, D. (2014). A conceptual and methodological critique of internet addiction research: Towards a model of compensatory internet use. Computers in Human Behavior, 31, 351-354.

Keles, B., McCrae, N., & Grealish, A. (2020). A systematic review: The influence of social media on depression, anxiety and psychological distress in adolescents. International Journal of Adolescence and Youth, 25(1), 79-93.

Koob, G. F., & Volkow, N. D. (2016). Neurobiology of addiction: A neurocircuitry analysis. The Lancet Psychiatry, 3(8), 760-773.

Kumar, V., Ashraf, A. R., & Nadeem, W. (2024). AI-powered marketing: What, where, and how?. International Journal of Information Management, *77*, 102783.

Leyton, M., & Vezina, P. (2013). Striatal ups and downs: Their roles in vulnerability to addictions in humans. Neuroscience & Biobehavioral Reviews, 37(9), 1999-2014.

Livingstone, S. (2018). Media literacy and the challenge of new information and communication technologies. The Communication Review, 7(1), 3–14.

Martin, K. (2018). Ethical implications and accountability of algorithms. Journal of Business Ethics, 160(4), 835–850.

Mathur, A., Acar, G., Friedman, M. J., Lucherini, E., Mayer, J., Chetty, M., & Narayanan, A. (2019). Dark patterns at scale: Findings from a crawl of 11K shopping websites. Proceedings of the ACM on Human-Computer Interaction, 3(CSCW), 1-32.

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. ACM Computing Surveys, 54(6), 1–35.

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. Big Data & Society, 3(2), 2053951716679679.

Montag, C., Lachmann, B., Herrlich, M., & Zweig, K. (2019). Addictive features of social media/messenger platforms and freemium games against the background of psychological and economic theories. International Journal of Environmental Research and Public Health, 16(14), 2612.

Müller, A., Mitchell, J. E., & de Zwaan, M. (2015). Compulsive buying. The American Journal on Addictions, 24(2), 132-137.

Nestler, E. J. (2014). Epigenetic mechanisms of drug addiction. Neuropharmacology, 76(Pt B), 259-268.

Newman, B. J., Shah, P., & Lauterbach, E. (2018). Who sees political ads? A model of exposure via Facebook. Journal of Communication, 68(2), 207-231

Pariser, E. (2011). The filter bubble: What the Internet is hiding from you. New York, NY: Penguin Press.

Partnership on AI. (2020). About the Partnership on AI. Partnership on AI. Retrieved from https://www.partnershiponai.org

Pasquale, F. (2015). The black box society: The secret algorithms that control money and information. Cambridge, MA: Harvard University Press.

Pasquale, F. (2015). The black box society: The secret algorithms that control money and information. Harvard University Press.

Ridgway, N. M., Kukar-Kinney, M., & Monroe, K. B. (2008). An expanded conceptualization and a new measure of compulsive buying. Journal of Consumer Research, 35(4), 622-639.

Robinson, T. E., & Berridge, K. C. (1993). The neural basis of drug craving: An incentive-sensitization theory of addiction. Brain Research Reviews, 18(3), 247-291.

Schwartz, B. (2004). The paradox of choice: Why more is less. New York, NY: HarperCollins.

Shin, M., & Park, E. (2019). How do human motivations and characteristics affect online shopping intention? Asia Pacific Journal of Marketing and Logistics, 31(1), 25-41.

Shin, D., & Park, Y. J. (2019). Role of fairness, accountability, and transparency in algorithmic affordance. Computers in Human Behavior, 98, 277–284.

Stilgoe, J., Owen, R., & Macnaghten, P. (2013). Developing a framework for responsible innovation. Research Policy, 42(9), 1568–1580.

Twenge, J. M., Martin, G. N., & Spitzberg, B. H. (2018). Trends in U.S. adolescents' media use, 1976–2016: The rise of digital media, the decline of TV, and the (near) demise of print. Psychology of Popular Media Culture, 8(4), 329-345.

Utz, S., Muscanell, N., & Khalid, C. (2019). Snapchat elicits more jealousy than Facebook: A comparison of Snapchat and Facebook use. Cyberpsychology, Behavior, and Social Networking, 18(3), 141-146.

Vogel, E. A., Rose, J. P., Roberts, L. R., & Eckles, K. (2014). Social comparison, social media, and self-esteem. Psychology of Popular Media Culture, 3(4), 206-222.

Voigt, P., & Von dem Bussche, A. (2017). The EU General Data Protection Regulation (GDPR): A practical guide. Springer.

Yang, Q., Liu, Y., Chen, T., & Tong, Y. (2019). Federated machine learning: Concept and applications. ACM Transactions on Intelligent Systems and Technology, 10(2), 1–19.

Volkow, N. D., & Morales, M. (2015). The brain on drugs: From reward to addiction. Cell, 162(4), 712-725.

Volkow, N. D., Koob, G. F., & McLellan, A. T. (2016). Neurobiologic advances from the brain disease model of addiction. New England Journal of Medicine, 374(4), 363-371.

Zuboff, S. (2019). The age of surveillance capitalism: The fight for a human future at the new frontier of power. PublicAffairs.

Zuckerman, M., & Kuhlman, D. M. (2000). Personality and risk-taking: Common biosocial factors. Journal of Personality, 68(6), 999-1029.

Chapter 8

Ethical Dilemmas in AI-Driven Advertising

Serim Paker[1]

Abstract

Artificial intelligence (AI) has transformed the advertising sector, improving efficiency, personalizing, and consumer involvement. Big data analytics, programmatic advertising, and automated decision-making combined in AI-driven advertising create tailored marketing campaigns with hitherto unheard-of accuracy. But these advances raise moral issues that create issues about consumer manipulation, privacy, prejudice, and openness. The capability of artificial intelligence to employ consumer information to allow hyper-personalization raises issues about consumer autonomy and data protection laws. Also, algorithmic bias within AI-powered advertising has the potential to reinforce social injustices, thus encouraging discriminative measures. Deepfakes, chatbots, and voice assistants used during advertising are also crossing moral limits because deceptive measures are employed to manipulate consumer behavior without open consent. Emphasizing the need to ensure strong regulations and corporate responsibility, this chapter critiques the moral issues raised about artificial intelligence-powered advertising. Some of the core issues like data privacy, fairness within algorithms, and disinformation are discussed along with some probable solutions like moral AI design principles, openness regulations, and measures to ensure regulatory compliance. At the end, the chapter supports a rational strategy that capitalizes on the capability of artificial intelligence but follows moral principles to encourage customer trust and eco-friendly advertising measures.

1. Introduction

AI has changed advertising, allowing for hyper-personalization, real-time targeting, and automated decision-making. While these innovations improve efficiency and consumer interaction, they raise ethical problems. Issues such as data privacy, bias, and consumer manipulation need a thorough

1 Asst.Prof Dr., Dokuz Eylül University, Izmir Türkiye, serim.paker@deu.edu.tr, https://orcid.org/0000-0002-8931-9039

https://doi.org/10.58830/ozgur.pub710.c3025

evaluation of AI's involvement in advertising. This chapter investigates these ethical quandaries, provides real-world examples of AI misuse, and proposes a paradigm for responsible AI-driven advertising.

2. The Role of AI in Advertising

Artificial intelligence (AI) has transformed the advertising industry by providing hyper-personalized marketing strategies and real-time data analysis. AI-powered systems can process massive volumes of consumer activity data, enabling firms to develop customized adverts that match individual interests and browsing behaviors. Automation in ad placement and campaign optimization has improved efficiency, lowering costs while increasing engagement. AI also improves creative processes by creating dynamic content, forecasting trends, and tailoring communications to specific audiences. While AI provides unprecedented opportunity for advertisers, it also raises ethical questions about privacy, bias, and the manipulation of customer preferences.

2.1. AI-driven Targeting and Personalization

Artificial Intelligence (AI) is substantially transforming various sectors, particularly e-commerce and healthcare, through its ability to deliver targeted and personalized experiences based on vast datasets. In the e-commerce industry, AI-powered personalization techniques employ complex algorithms to scan consumer behavior and preferences to present highly personalized product recommendations and content. This has the advantage of enhancing customer satisfaction, engagement, and loyalty, ultimately establishing market trends within the industry (Raji et al., 2024) emphasize that AI's ability to generate personalized consumer experiences not only enhances sales but also brand loyalty through effectively meeting the individual customer needs.

AI application in **healthcare** extends the use of conventional diagnostics and therapy strategies to include personalized medicine and patient care. AI algorithms analyze genetic and demographic data to ascertain patients best positioned to benefit from specific interventions, optimizing the interventions' efficacy(Pawar et al., 2023; Weerarathna et al., 2023). Weerarathna et al. (2023) , for instance, refer to the use of AI models to predict patient responses to chemotherapy to allow personalized treatment strategies. Furthermore, Kokudeva et al. (2024) also investigate the use of AI to help determine targets and optimize the treatment protocol using machine learning, showing AI's capability to generate personalized therapeutic strategies.

Despite the amazing advantages brought about through AI in targeting and personalization, there are issues that remain, particularly in the shape of ethics issues and data privacy. As AI marketing continues to evolve further, the equilibrium between applying consumer information to create profits and consumer trust hangs in the balance. Gupta et al. (2021) are concerned about the ethics of AI marketing, citing the necessity for responsibility and openness from businesses applying AI tools. This attitude supports the need of ethical frameworks as artificial intelligence is more ingrained in many fields, not only business and marketing but also including tailored healthcare plans and drug development.

In addition, the integration of AI technologies has far-reaching implications for healthcare providers. AI's ability to provide real-time analysis using wearable devices and point-of-care tests provides healthcare providers the ability to deliver better patient outcomes along with system efficiency improvements (Yammouri & Lahcen, 2024). Such innovation is moving toward the future where real-time analysis means timely interventions further individualizing healthcare delivery. However, the technologies also raise the need to ensure robust data handling practices to safeguard patient privacy while making the best use of the data (Wasilewski et al., 2024).

In summary, overall, the application of AI to targeting and personalization is revolutionizing industries through higher customer involvement and patient care optimization. But the intersection of technology, ethics, and consumer privacy has to be balanced carefully to ensure that the full benefit of AI can be achieved while safeguarding consumer interests.

2.2. Advertising with Big Data Analytics

Particularly under the cover of programmatic advertising and big data analysis, the junction of artificial intelligence (AI) and targeting and personalizing has been much studied. Programmatic advertising depends on artificial intelligence algorithms and vast amounts of data to provide customized advertising that will help to make marketing effective and unique. AI-powered platforms scan consumer behavior, preferences, and demographic data to automate the buying and placement of the advertising in real-time to generate highly targeted marketing strategies that enhance the user experience and conversion rate. According to Holloway (2024), the use of AI and big data analysis under marketing campaigns has the potential to significantly enhance customer satisfaction through personalized offers that appeal to individual customers to generate lasting loyalty.

Big data analytics plays a critical role in the effectiveness of programmatic advertising. Data-driven insights allow marketers to craft compelling campaigns that are precisely targeted based on consumer behavior analysis. The utilization of personal data gathered from various sources, including Internet of Things (IoT) devices, social media platforms, and online transactions, enables marketers to deliver advertisements tailored to the needs and preferences of their audience (Khrais, 2020; Oh et al., 2019). By effectively combining AI's capabilities with extensive data sources, marketers can maximize their outreach and engagement while minimizing advertising wastage.

But the widespread use of personal information raises privacy-related ethics issues and challenges. As Oh et al. (2019) further clarify, brokers accumulate large amounts of personal information, balancing the need to provide personalized marketing with the need to protect consumer privacy. Overcoming these challenges involves establishing an open framework that governs the collection and use of personal information to protect consumer trust and ensure regulatory compliance. The new landscape demands that businesses employ robust data handling practices to ensure the ethical use of AI and consumer information through programmatic advertising. Ethical issues must be top priority, as evidenced through various research pieces regarding the balance between privacy and personalization (Park et al., 2023).

Moreover, AI-driven personalization extends beyond mere advertisement targeting to impact consumer behavior on a broader scale. Studies suggest that personalized promotions, such as mobile coupons, can enhance customer engagement and influence purchasing decisions positively (An et al., 2021; Huang et al., 2023). As Oh et al. Oh et al. (2019) elaborate, data brokers collect vast amounts of personal information, creating a tension between the demand for personalized marketing and the necessity to protect consumer privacy. Addressing these concerns involves establishing a transparent framework that governs the collection and usage of personal data to maintain consumer trust and compliance with regulatory standards. The evolving landscape necessitates that businesses employ robust data management practices, ensuring ethical use of AI and consumer data in programmatic advertising. Ethical considerations must be at the forefront, as underscored by various studies on the balance between personalization and privacy (Park et al., 2023).

In addition to this, AI-powered personalization breaks the limits of mere advertising targeting to influence consumer behavior on a greater scale. Studies prove that personalized offers such as mobile coupons can promote higher customer engagement and influence purchasing behavior positively(An et al., 2021; Huang et al., 2023). The competitive advantage gained by tailoring marketing messages based on consumer profiles aligns marketing strategies with individual consumer preferences, ultimately driving higher conversion rates and more effective brand interactions (Bhuiyan, 2024; Sodiya et al., 2024).

To summarize, the confluence of artificial intelligence-driven personalization and programmatic advertising with big data analytics gives enormous opportunity for marketers to effectively improve their campaigns. Enterprises have the ability to utilize these technologies in order to provide individualized experiences while simultaneously navigating the essential problems of ethical data usage and privacy protection. This will provide a sustainable and responsible approach to marketing in the digital era.

2.3. AI-Enhanced Targeting and Personalization, Programmatic Advertising, AI-Generated Content, Chatbots, and Voice Assistants

Particularly in the areas of personalizing through targeting, programmatic advertising, AI-generated content, chatbots, and voice assistants, the integration of artificial intelligence (AI) technologies has revolutionized many industries. AI combined with big data analytics offers effective marketing solutions and improves user interactions on several digital platforms.

2.3.1. AI-driven Targeting and Personalization with Programmatic Advertising

AI-driven targeting has reshaped marketing strategies, particularly programmatic advertising, which uses AI algorithms to automate ad buying and placement in real time. This method enables businesses to analyze consumer data and behaviors, resulting in targeted advertisements that boost user engagement and conversion rates. Big data analytics improves these capabilities by facilitating the extraction of relevant consumer insights, allowing marketers to tailor their strategies more effectively based on identified preferences and purchasing patterns. However, this reliance on personal data requires strong ethical considerations, particularly concerning privacy, data security, and consumer trust (Kokudeva et al., 2024; Pawar et al., 2023; Weerarathna et al., 2023).

2.3.2. AI Content Generation and Its Consequences

AI-generated content (AIGC) has gained extensive interest based on the prospect of automating the production of content using various forms like text, imagery, and video. Research indicates that the quality of AI-generated content has a direct connection to the extent to which it will be used and accepted, especially in the learning sector where it has proven to be linked to greater learning tool satisfaction amongst learners (Holloway, 2024; Khrais, 2020). Research indicates that AI has the capability to produce new and personalized content that responds to certain user requests, further cementing the use of AI in personalized marketing strategies. The perception of AI-generated content is however complex; users are highly cautious about AI-generated content that has proven to be lower compared to human-generated content (Altay & Gilardi, 2024; Zhang & Gosline, 2023). This makes users avoid using AI tools to generate content despite the fact that AI tools are highly efficient. (Altay & Gilardi, 2024; Zhang & Gosline, 2023).

Detecting AI-generated content poses additional challenges, particularly in academic and professional writing contexts where integrity is paramount. Current studies demonstrate that while AI content detectors can identify machine-generated text with reasonable accuracy, they frequently misclassify human-generated contenas AI, raising concerns about their reliability in educational assessments and publishing (Elkhatat et al., 2023; Yadav & Rathore, 2023). This misclassification highlights the need for more nuanced detection tools capable of differentiating between human and AI-generated texts, especially in contexts involving mixed authorship (Howard (Howard et al., 2024).

2.3.3. Voice Assistants and Chatbots in Consumer Interactions

Chatbots and voice assistants are core components of AI-powered personalization. Chatbots communicate with users through textual conversations, often within the context of a service-related scenario, whereas voice assistants employ voice recognition mechanisms to create a more naturalistic user experience(Khedekar et al., 2023; Sezgin et al., 2020). These two tools have been used within various industries, including education and healthcare, where they facilitate efficient communication and automate operations (Terzopoulos & Satratzemi, 2020). Research has shown that adults and children alike are attracted to the ease of use of the AI tools, which are capable of performing functions from answering questions to managing routine operations (Terzopoulos & Satratzemi, 2020; Khedekar et al., 2023). The increased usage of the tools signifies a shift toward more interactive and reactive digital experiences that are personalized to the individual needs of users.

In summary, overall, the convergence of programmatic advertising, AI-powered personalization, voice assistants, AIGC, and chatbots has the transformative capability to benefit both users and businesses. That being said, there are certain issues surrounding ethics, social attitudes, and content identification that need to be addressed as these technologies mature further. Navigating through the complexities will be essential to unlock the full benefits that AI has to offer to deliver higher user satisfaction and engagement.

2.4. AI in Campaign Management and Budget Optimization

Artificial intelligence (AI) is being increasingly implemented in marketing, which is causing a number of aspects of campaign management and budget optimization to undergo ongoing transformations. A significant contribution to the improvement of operational efficiency, personalization, and the overall impact of marketing strategies has been made by the synergy that exists between artificial intelligence and marketing activities.

2.4.1. AI in Campaign Management

AI technologies have demonstrated significant potential in revolutionizing campaign management by optimizing resource allocation and enhancing strategic decision-making processes. AI algorithms facilitate real-time analysis and forecasting, allowing marketers to adjust campaign parameters and allocate budgets efficiently in response to changing market conditions (Egorenkov, 2022). The integration of AI not only streamlines campaign execution but also improves the accuracy of marketing decisions, driving better engagement and enhancing customer experiences (Lyndyuk et al., 2024b). For instance, Țîrcovnicu and Haţegan (2023) discuss how AI-driven data analytics refine customer interactions, fostering a more effective marketing environment across various sectors, including retail.

The effectiveness of AI in these domains stems from its ability to process vast amounts of data and uncover insights that would be challenging to identify manually. Heins (2022) and Arbaiza et al. (2024) emphasize that AI can enhance campaign personalization by analyzing consumer behavior patterns, enabling advertisers to deliver tailored messaging that resonates with specific audience segments. This capability not only enhances user engagement but also optimizes advertising spend, leading to improved return on investment (ROI) (Ledro et al., 2022).

2.4.2. Budget Optimization through AI

AI-driven budget optimization is another pivotal aspect that contributes to the effectiveness of marketing campaigns. Businesses can utilize AI tools to simulate different budget scenarios, allowing for data-driven decisions on where to allocate resources for maximum impact (Egorenkov, 2022). The predictive capabilities of AI can help organizations forecast campaign performance based on historical data, leading to smarter financial decisions that align with strategic marketing goals (Noranee & Othman, 2023). The ability to forecast returns on marketing investments allows brands to allocate budgets dynamically, ensuring funds are utilized in the most effective areas of campaign execution.

Research shows that businesses leveraging AI for campaign management not only maintain a competitive edge but also achieve higher levels of automation and efficiency (Zancan et al., 2023). Organizations can automate routine marketing processes, freeing up resources and enabling teams to focus on strategic initiatives (Arbaiza et al., 2024). The insights garnered from AI can inform everything from media buying strategies to content creation, enhancing the precision of marketing actions and reducing wasted spend in advertising.

2.4.3. Ethical Considerations in AI-Driven Campaigns

Even if artificial intelligence brings benefits for budget control and campaign management, ethical issues have to be resolved to guarantee appropriate AI application in marketing. Using personal data for targeted advertising asks issues about customer privacy and consent, hence open data policies are necessary to develop confidence with consumers (Adebayo, 2024). Organizations have to create thorough ethical rules to control the use of artificial intelligence in marketing plans and maximize its advantages without endangering consumer privacy or confidence, as Chang and Ke (2023) emphasize.

Finally, the way artificial intelligence helps with budget control and campaign management greatly improves the capacity of marketing teams in the current environment of competitiveness. AI technologies are becoming essential tools for marketers looking for accuracy, efficiency, and ethical standards in their campaigns since they can analyze enormous datasets, forecast results, and automate procedures. To completely realize its transforming power in marketing, constant research and practice in artificial intelligence must negotiate data security and ethical consequences.

3. Ethical Dilemmas in AI-Driven Advertising

In the rapidly evolving landscape of AI-driven advertising, ethical dilemmas have emerged as a subject of considerable concern among scholars and practitioners alike. The integration of artificial intelligence in advertising methods has led to significant advantages in personalization and efficiency, but it also raises critical ethical issues, particularly surrounding consumer privacy, algorithmic bias, and transparency. Camilleri (2024) implies, in their research, that all those who are involved in the research, development and maintenance of AI systems, have social and ethical responsibilities to bear toward their consumers as well as to other stakeholders in society.

One prominent ethical issue in AI-driven advertising is the lack of transparency regarding how AI algorithms function and make decisions. Sometimes unaware that they are interacting with artificial intelligence systems, consumers wonder about their autonomy and the possibility of manipulation without informed permission. Many people may not understand the consequences of being targeted by AI-driven adverts, hence mistrust between customers and companies can result. (Kumar & Suthar, 2024). Moreover, algorithmic bias raises another alarming aspect since artificial intelligence systems can reinforce current society prejudices seen in their training data. Such prejudices can result in biased advertising methods, therefore supporting rather than questioning preconceptions. (N. Singh, 2023; Ziakis & Vlachopoulou, 2023). Brands must take a proactive approach in managing and auditing these algorithms to ensure fairness and prevent the perpetuation of harmful biases. (N. Singh, 2023).

Another critical aspect concerns consumer data privacy. The use of vast datasets allows AI algorithms to tailor advertisements to specific consumer behaviors and preferences, yet it raises pressing questions about data ownership and consent. Ethical marketing frameworks must navigate the tension between maximizing personalized consumer experiences and respecting individual privacy rights. As AI technologies scale, the implications for data protection and ethical governance become increasingly complex (Camilleri, 2023; Sharma, 2023). Business practices need to prioritize transparency and accountability, ensuring that consumers can make informed decisions about their data.

Moreover, how AI depicts women in advertising presents gender portrayal and societal norm-related moral issues. The employment of female-presenting chatbots and advertising characters to generate advertising personas presents issues about the reinforcement of gender-related stereotypes. The employment of AI has the capability to encourage diversity but must be employed prudently to avoid the reinforcement of gender-related stereotypes within advertising strategies (Greguš & Škvareninová, 2023; Kriaučiūnaitė-Lazauskienė, 2023). The responsibility lies with the advertisers to ensure that AI tools are employed to encourage inclusivity rather than exclusivity (Kriaučiūnaitė-Lazauskienė, 2023).

Overall, AI advertising has the potential to revolutionize marketing strategies through enhanced personalization and efficiency but has complex ethical challenges. These include defending consumer privacy, addressing algorithmic bias, and ensuring gender equity in representations. Structuring AI marketing strategies around ethical principles is crucial for maintaining consumer trust and achieving sustainable advertising practices that reflect societal values and norms.

3.1. Consumer Manipulation and Persuasion

Within the field of consumer behavior, the expression "Consumer Manipulation and Persuasion" captures the tactics that marketers deploy in order to influence the decisions that consumers make regarding their purchases. There are two essential ideas that come to light under this framework: "*Exploiting Consumer Vulnerabilities*" and "*AI-Based Subconscious Persuasion Techniques*".

3.1.1. Exploiting Consumer Vulnerabilities

Marketers often capitalize on consumer vulnerabilities, which can range from emotional states to cognitive biases. Vulnerable populations, including those experiencing stress, low self-esteem, or uncertainty, may be particularly susceptible to persuasive techniques. For instance, advertising can employ emotional appeals such as fear or guilt to prompt consumers to make purchasing decisions that they are otherwise unwilling to undertake (Hibbert et al., 2007). The effectiveness of such tactics relies upon consumers' knowledge regarding persuasion tactics. If consumers are conscious that an attempt to manipulate them has been made, then they are likely to be defensive, perhaps diffusing the emotional appeal meant to be created through the advertisement (Alenazi, 2015). Successful manipulation then tends to balance the presentation of emotional appeals and the consumer defenses based upon persuasion knowledge—the set of knowledge regarding marketing tactics(Kirmani & Zhu, 2007).

Moreover, AI technologies have further changed the means through which consumer susceptibilities can be exploited. Machine learning algorithms scan consumer data to find emotional triggers and susceptibilities to allow marketers to produce advertising that targets the emotional states and susceptibilities of specific consumers effectively(Hacker, 2021). This targeting has an ethical issue because the practice has the possibility to create an exploitative situation where consumers are directed toward making specific choices through repeated reinforcement of susceptibilities unbeknownst to them. Hence, consumer vulnerability exploitation has a two-edged sword character: it can be employed to promote sales but has to be handled using ethics to avoid manipulation.

3.1.2. AI-Based Subconscious Persuasion Techniques

AI-based subconscious persuasion techniques represent an innovative intersection of technology and psychology that facilitates subtle influence on consumer behavior. Marketers are increasingly deploying AI to create environments where consumers are subtly guided toward specific products without their conscious awareness. This approach often involves employing persuasive cues that resonate unconsciously with consumers, thereby bypassing their direct defenses (Isaac & Grayson, 2019). For example, advertisements might utilize color psychology or other subliminal techniques to provoke desired responses, influencing perceptions and purchasing behavior at a subconscious level (Lim et al., 2020).

One fascinating aspect of AI-driven persuasion is its capacity to adapt continuously based on real-time consumer behavior and interactions. Algorithms can fine-tune advertising strategies by learning from consumer reactions, optimizing the presentation of messages to elicit desired subconscious responses (Hacker, 2021). However, this raises profound ethical questions concerning informed consent and the potential for manipulation. Consumers may not be aware of how their preferences are shaped by AI, creating what some researchers term a "manipulation loop," where the technology's influence perpetuates consumer vulnerabilities without transparency (Ryu, 2024).

Furthermore, the application of persuasion knowledge becomes crucial in understanding these subconscious techniques. Consumers equipped with high levels of persuasion knowledge may become more vigilant against AI manipulations, potentially leading to a backlash against brands perceived to exploit such technologies for manipulation. Conversely, lower levels of persuasion knowledge may leave consumers more susceptible to subconscious influences, illustrating a critical area for further research and ethical debate (Kirmani & Zhu, 2007).

In conclusion, "Exploiting Consumer Vulnerabilities" and "AI-Based Subconscious Persuasion Techniques" highlight the nuanced and sometimes contentious relationship between marketing strategies and ethical consumer engagement. As AI continues to evolve, understanding and navigating these dynamics will be essential for both marketers and consumers, fostering a marketplace that prioritizes ethical transparency and consumer empowerment.

3.2. Privacy and Data Protection

In a society that is becoming more and more digital, privacy and data protection have become top priorities especially with the development of artificial intelligence (AI) and its uses in many different fields. The vast capabilities of AI-driven tracking systems, which enable large data collecting, are increasing the ethical consequences connected to consumer privacy. Furthermore, more important than ever are legislative protections against possible violations resulting from artificial intelligence technology in advertising: the General Data Protection Regulation (**GDPR**) and the California Consumer Privacy Act (**CCPA**).

3.2.1. AI-Driven Tracking Systems and the Risks of Mass Data Collection

AI-driven tracking systems have revolutionized how businesses interact with consumers by allowing unparalleled access to data on user behavior, preferences, and interactions. Such systems utilize various methods, including cookies, mobile app tracking, and social media monitoring, to collect vast amounts of personal data. This mass data collection raises significant privacy concerns, especially regarding how this data is stored, analyzed, and utilized without obtaining informed consent from consumers (Arbaiza et al., 2024; Xu et al., 2024).

The risks associated with these practices include potential breaches of data privacy, unauthorized usage of personal information, and even identity theft. When organizations gather substantial troves of data using AI, they may inadvertently expose sensitive information, making it a target for cybercriminals. As noted by Huda Huda et al. (2024), the regulatory landscape still struggles to keep pace with technological advancements, creating a gap where consumer privacy can be jeopardized and leading to systemic vulnerabilities in how personal data is safeguarded (Idoko et al., 2024). Thus, while AI facilitates better advertising and consumer engagement, it also invites ethical and legal dilemmas about the extent and manner of data collection (Eriksson, 2024).

3.2.2. GDPR, CCPA, and the Ethical Violations of AI in Advertising

The GDPR and CCPA represent critical legal frameworks designed to protect consumer privacy rights. The GDPR, implemented in the European Union, establishes stringent rules on data processing, requiring organizations to collect personal data responsibly and transparently (Reddy et al., 2020). Similarly, the CCPA provides California residents with the right to know what personal information is collected, allowing them to opt out of data sharing and enabling them to control the utilization of their data (Jin & Skiera, 2022).

Despite these regulations, ethical violations often occur in the context of AI in advertising. The potential for misalignment between consumer expectations and how organizations utilize AI for targeted advertising presents a significant challenge. AI systems may exploit loopholes in these regulations or misinterpret consent, leading to instances where consumers are unaware of how their data is being manipulated for commercial gain (Hoxhaj et al., 2023). There is a growing concern that these advertising practices can lead to ethical violations, where the consumer's autonomy and data rights are undermined, highlighting the need for stricter compliance and accountability measures among organizations deploying AI technologies (Williamson & Prybutok, 2024).

Furthermore, while health information, sensitive personal data, and biometrics are particularly vulnerable, organizations often lack robust mechanisms to safeguard this data effectively, leading to further ethical and legal challenges (Murdoch, 2021) and raising questions about the adequacy of current regulatory frameworks in addressing these complexities comprehensively (Liu et al., 2024). Continuous monitoring and adaptation of these laws are necessary to align with the rapidly advancing landscape of AI technology and its impact on consumer privacy rights.

In conclusion, the intersection of AI and data protection is fraught with challenges that necessitate a careful approach to consumer privacy. Legal frameworks such as GDPR and CCPA must evolve alongside AI advancements to ensure they effectively mitigate risks associated with data collection and enhance ethical compliance in advertising practices.

3.3. Bias and Discrimination

Bias and prejudice within artificial intelligence (AI) provide substantial ethical dilemmas with far-reaching consequences for people and society at large. Algorithmic bias, a consequence of defective machine-learning methodologies, arises when AI systems unintentionally mirror prevailing cultural preconceptions embedded in their training data. The systematic review emphasizes the importance of ongoing research, highlighting the complex interplay between bias, technological advancements, and societal impacts. The thorough analysis emphasizes the complexities of bias in AI algorithms, highlighting the critical importance of addressing these issues in future developments(Fazil et al., 2023). This section explores two critical aspects: "Algorithmic Bias and Its Ethical Implications" and "The Dangers of Over-Personalization Limiting Consumer Options."

3.3.1. Algorithmic Bias and Its Ethical Implications

Algorithmic bias refers to the systematic and unfair discrimination that occurs when AI systems produce outcomes that are prejudiced against certain groups, often based on race, gender, or socioeconomic status. This bias can originate from various sources, including the datasets used to train AI models, which may be unrepresentative or reflect historical biases (Fazil et al., 2024; Min, 2023). For instance, predictive policing algorithms have been criticized for disproportionately targeting minority communities due to the biased historical crime data upon which they were trained (Min, 2023). The implications of this bias extend to various sectors, including hiring practices, loan approvals, and healthcare diagnoses, posing ethical concerns about fairness and equal treatment (Drage & Mackereth, 2022; Osasona et al., 2024).

The ethical ramifications of algorithmic bias are extensive. When certain demographics receive less favorable outcomes due to biased algorithms, issues of justice and equity are called into question. This undermines trust in AI technologies and raises concerns regarding accountability—if an AI system discriminates, who is responsible? Moreover, the continued implementation of these biased systems perpetuates existing inequalities and has a cascading effect on public perception of technology (Ferrara, 2023; Sreerama & Krishnamoorthy, 2022). Addressing algorithmic bias thus necessitates a multifaceted approach that includes not only technical interventions, but also ethical guidelines and regulatory frameworks aimed at ensuring equitable treatment for all groups (Fazil et al., 2024; Jobin et al., 2019).

3.3.2. The Risks of Excessive Personalization Narrowing Consumer Choices

Excessive personalization, while often touted as a means to enhance user experience, can inadvertently narrow consumer choices through algorithmic filtering. When AI systems are designed to curate content tailored to individual user preferences, they can lead to echo chambers where consumers are exposed primarily to information and products that align with their existing beliefs and desires (Chu et al., 2022). This phenomenon can constrain the diversity of choices available to consumers, effectively limiting their exposure to novel ideas or alternatives that do not fit their predefined profiles (Aladeen, 2023).

The implications of this narrowing effect extend to areas such as advertising, content consumption, and social media interaction. Research has shown that as algorithms refine their targeting capabilities, they tend to reinforce existing consumer behaviors rather than encourage exploration and diversification (Christanto et al., 2024; Sun et al., 2020). As a result, consumers may find themselves trapped within a narrow perception of available options, which can adversely affect their decision-making processes and overall satisfaction with their experiences (Xie & Huang, 2023).

Moreover, this excessive personalization raises ethical concerns regarding autonomy and informed consent. Consumers may unknowingly surrender their agency as algorithms dictate the scope of their choices (Rosales & Fernández-Ardèvol, 2019). This is exemplified in the realm of targeted advertising, where data-driven algorithms prioritize immediate sales over delivering a broader spectrum of relevant alternatives. Ultimately, the risks associated with excessive personalization necessitate a careful evaluation of the balance between enhancing user experiences and maintaining the integrity of consumer choice (Illia et al., 2022).

In conclusion, addressing bias and discrimination in AI involves a two-pronged exploration of algorithmic bias and the risks posed by excessive personalization. Both aspects highlight the need for comprehensive ethical standards and regulatory measures to facilitate the deployment of AI technologies in a manner that promotes fairness, transparency, and consumer choice.

3.4. Autonomous Decision-Making in Advertising

Autonomous decision-making in advertising refers to the use of artificial intelligence (AI) systems that operate independently or with limited human input to create, manage, and optimize advertising campaigns. AI's ability to analyze vast amounts of data and execute complex strategies has led to its growing use in advertising practices. This discourse focuses on two primary areas: "AI Surpassing Human Decision-Making in Advertising

Strategies" and "Ethical Concerns Regarding Consumer Autonomy and Misinformation"(Lyndyuk et al., 2024a).

3.4.1. AI Surpassing Human Decision-Making in Advertising Strategies

AI technologies have the potential to surpass human decision-making capabilities primarily through their proficiency in processing large datasets at speeds and accuracies unattainable by humans. This computational superiority allows AI to analyze consumer behavior, preferences, and engagement patterns, leading to highly targeted advertising tactics. For instance, AI systems can predict market trends and optimize media spending in real-time, leading to enhanced advertising effectiveness and cost-efficiency compared to traditional methods (Kumar & Suthar, 2024; N. Singh, 2023).

As stated by Arbaiza et al. (2024) AI's ability to handle predictive analysis significantly improves campaign relevance by customizing content to individual users' needs and preferences. These advancements allow marketers to segment audiences more effectively and deploy personalized advertisements, maximizing engagement and conversion rates while continuously learning from performance data (Kumar & Suthar, 2024; N. Singh, 2023). Furthermore, AI's capacity to manage multi-channel campaigns ensures consistent messaging across platforms, an aspect that can be challenging for human-managed strategies due to the complexity involved. This shift toward AI-dominated decision-making is transforming the advertising landscape, where speed and precision may outweigh human intuition and experience.

However, there are limitations to AI's effectiveness, particularly concerning its reliance on historical data. If the training data is biased or unrepresentative, the resultant advertising strategies could reinforce existing stereotypes or create misleading narratives (Ziakis & Vlachopoulou, 2023). Thus, while AI has the potential to enhance decision-making processes, it is crucial to ensure that the data used for training is comprehensive and free from bias to avoid undermining the ethical integrity of advertising outcomes.

3.4.2. Ethical Concerns Regarding Consumer Autonomy and Misinformation

The escalation of autonomous decision-making in advertising raises numerous ethical concerns, particularly regarding consumer autonomy and the potential for misinformation. One of the primary issues is that consumers may not be fully aware of how AI-driven advertisements are shaping their decisions. The overwhelming personalization capabilities of AI can effectively manipulate consumer choices, often steering them toward products or services that align with commercial interests rather than genuine consumer need or desire (Ziakis & Vlachopoulou, 2023). As a result, individuals might experience a diminished sense of agency, as they encounter a narrowing range of choices predominantly influenced by AI algorithms (Ziakis & Vlachopoulou, 2023).

Moreover, the utilization of misleading advertisements poses significant risks of misinformation, particularly when AI systems are programmed to prioritize clicks and engagement over factual correctness. Research indicates that inaccurate information in advertisements can lead to misguided consumer behaviors, ultimately affecting purchase intentions and undermining informed decision-making (Singh, 2023; Ziakis & Vlachopoulou, 2023). The propensity for AI-generated advertisements to propagate misinformation further complicates the landscape, necessitating robust scrutiny.

To address these ethical concerns, it is imperative to incorporate transparency and accountability into AI-driven advertising practices. Businesses must ensure that consumers are aware of how their data is being used, adopting models that prioritize ethical marketing and empower consumer autonomy (Kumar & Suthar, 2024; al., 2023). Implementing explainable AI methods can enhance consumer comprehension of AI-generated recommendations and advertisements, fostering trust and improving decision-making processes. Furthermore, practicing stringent checks on the veracity of advertisement claims can mitigate misinformation risks and promote ethical standards in advertising (Camilleri, 2023; Sharma, 2023).

In conclusion, while autonomous decision-making in advertising facilitated by AI offers remarkable advantages in efficiency and effectiveness, it also necessitates a critical examination of ethical considerations related to consumer autonomy and the dissemination of accurate information. Balancing innovation with responsibility will be vital in ensuring that advertising serves to enhance consumer experiences rather than compromise them.

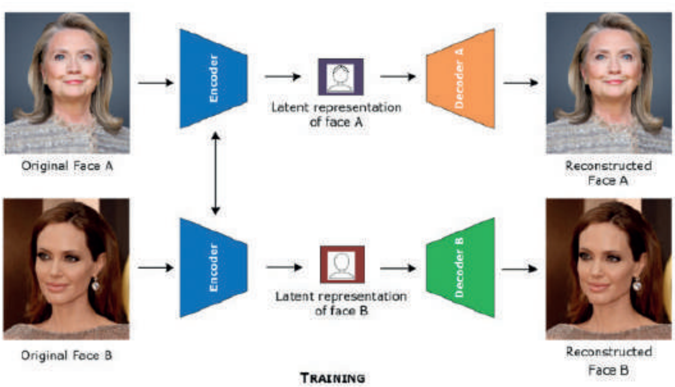
4. Cases: Unethical Uses of AI in Advertising

The exploration of unethical uses of artificial intelligence (AI) in advertising unveils troubling case studies that illustrate serious ethical dilemmas, privacy infringements, and manipulative practices. This analysis primarily delves into four significant cases: the Cambridge Analytica scandal involving political microtargeting, Facebook's AI-driven behavioral advertising mechanisms, the rise of deepfake technology in advertising and the associated ethical concerns, and the problematic use of AI chatbots that engage in deceptive marketing practices.

4.1. The Cambridge Analytica case, which came to light in 2018, is emblematic of the disturbing intersection of data privacy and political advertising (Corrêa et al., 2023). The company exploited personal data acquired from millions of Facebook users without their consent to create detailed psychological profiles and execute tailored political campaigns. This microtargeting strategy raised profound ethical questions regarding user consent and data ownership, exposing vulnerabilities within the regulatory frameworks governing data privacy (Chouaki et al., 2022).

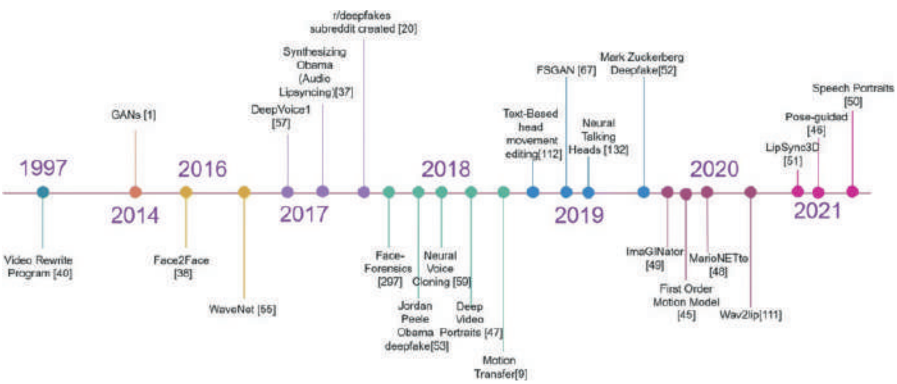
The unethical manipulation of such data facilitated the dissemination of targeted misinformation and played a significant role in shaping the political landscape during elections (Ali et al., 2019). Cambridge Analytica's practices prompted increasing scrutiny and calls for reform in political advertising, leading to legislative measures intended to protect users from similar exploitative strategies in the future (Eriksson, 2024).

4.2. Facebook's AI-driven behavioral advertising mechanisms further complicate the ethical landscape of digital marketing. The platform's algorithms optimize advertisement delivery based on user engagement and preferences inferred from vast quantities of personal data. However, these practices often lack transparency, leading to issues such as discrimination and manipulation of user sentiment (Andreou et al., 2019). Research suggests that while Facebook aims to connect advertisers with relevant users, this often leads to echo chambers that reinforce existing beliefs and biases, fostering political polarization (Cotter (Cotter et al., 2021)et al., 2021). The opaque nature of ad targeting erodes trust among users and raises social responsibility concerns regarding how advertisers can exploit algorithmically derived data to shape perceptions and behavior without user awareness (Ali et al., 2019).



4.3. The advent of deepfake technology has introduced another layer of ethical complexity in advertising. Deepfakes, which employ AI to create hyper-realistic yet fictitious representations of individuals, present significant risks in terms of misinformation and deceptive advertising practices (Pizzi et al., 2023). This technology raises ethical concerns about authenticity and consumer trust as advertisers might use deepfakes to present misleading narratives or endorsements from individuals without their consent (Wiese et al., 2020). The potential for deepfakes to fabricate celebrity endorsements or mislead consumers about product efficacy poses risks not just to individuals but also undermines the integrity of brands and the advertising industry as a whole (Pizzi et al., 2021). The deceptive nature of such representations necessitates strict regulations to address the ramifications of false advertising and protect consumers from manipulative practices (Kish, 2020). The earliest example of manipulated multimedia content oc-curred in 1860 when a portrait of southern politician JohnCalhoun was skillfully manipulated by replacing his head with that of US President for propaganda purposes and evolved rapidly until present(Masood et al., 2022). The timeline of key developments can be seen at Figure1.

Figure1. Timeline of Key Developments.



4.4. AI chatbots, which have become increasingly prevalent in marketing, also present ethical dilemmas through manipulative practices. These chatbots, often programmed to engage users and facilitate transactions, may employ strategies to influence consumer behavior without disclosing their artificial nature. Studies indicate that chatbots can foster relationships with consumers that blur the lines between human interaction and AI engagement, often to the latter's advantage (Arbaiza et al., 2024). For example, the anthropomorphism of chatbots—giving them human-like traits—can lead consumers to lower their defenses, making them more susceptible to marketing tactics that might otherwise be viewed skeptically (Pizzi et al., 2023). This degree of manipulation necessitates a balanced approach that embraces technological advancement while upholding ethical standards in consumer interactions.

In conclusion, the unethical uses of AI in advertising highlight significant challenges regarding privacy, transparency, and consumer protection. Each case study demonstrates the necessity for frameworks that ensure ethical practices in the use of AI technologies in marketing. The convergence of technological innovation and ethical responsibility forms the basis for re-evaluating advertising strategies, emphasizing the need for regulatory oversight that protects consumers and fosters trust in digital marketing landscapes. These illuminating case studies reflect critical issues that demand scholarly attention and policy intervention to safeguard public interests in the evolving world of AI-powered advertising.

5. Ethical AI Advertising Framework: Principles and Recommendations

The following are some of the recommendations that could be put into consideration.

5.1. Transparency & Explainability

As advertising increasingly incorporates AI-driven techniques, transparency becomes paramount. Consumers should be empowered to understand how algorithms influence the ads they encounter. Explainability relates to the ability to uncover how decisions are made in AI systems, allowing stakeholders to grasp the inner workings of these models (Cary et al., 2024). Research emphasizes the importance of clear communications from companies regarding the algorithms they employ, including the data inputs that drive ad placements (Sreerama & Krishnamoorthy, 2022). Practitioners must aim for transparency not merely as a compliance measure but as a fundamental principle of ethical practice in AI advertising (Mehrabi et al., 2019). By promoting informed consumer consent, organizations can foster trust and accountability within the advertising ecosystem (Fletcher et al., 2021).

5.2. Fairness (Equity) & Bias Mitigation

Maintaining fairness is not only a basic need of ethical artificial intelligence in marketing but also an optional extra feature. The algorithms themselves and the data used for training are among the several sources of bias that might mirror society prejudices (Bellamy et al., 2019; Ferrara, 2023). Methods such as fairness metrics enable one to evaluate the equity of AI advertising systems by means of which one can spot and minimize disparities (Albaroudi et al., 2024). Attaching fair results requires effective strategies including data preprocessing, algorithmic transparency, and varied representation (Sreerama & Krishnamoorthy, 2022). To address the complexity of bias in artificial intelligence systems (Bellamy et al., 2019), an interdisciplinary approach comprising cooperation among technologists, advertisers, and social scientists is absolutely essential.

Data Privacy and Consumer Control

Using artificial intelligence in advertising magnifies consumer data privacy issues and calls for strict data protection policies. Consumers have to keep control over their personal data and make wise decisions on the usage of it (Zhao, 2024). Regulatory frameworks should mandate organizations to implement robust data governance practices that respect consumer preferences, minimizing risks related to data misuse (Cheong et al., 2023; Tillu et al., 2023b). By means of data for advertising personalization, the integration of technologies like anonymization and encryption helps to strengthen privacy measures so ensuring ethical standards are maintained(Tillu et al., 2023a). Maintaining consumer autonomy will not only help to increase the legitimacy of advertising markets but also encourage adherence to legal rules about data privacy (Padmanaban, 2024).

5.3. Regulatory Compliance and Corporate Liability

Organizations have to keep ethical standards going beyond simple compliance while matching their AI advertising practices with current legal systems. Companies should aggressively modify their strategies to fit regulatory needs and build a culture of corporate responsibility as the terrain of AI control is fast changing (Chin et al., 2023; Tillu et al., 2023b). This covers following accepted ideas of justice and responsibility as well as creating an environment that gives ethical issues top priority for the application of artificial intelligence technologies(Padmanaban, 2024). Companies can reduce the risks related to algorithmic bias and help to build public confidence in AI systems by actively participating in compliance and proving social responsibility (Albaroudi et al., 2024; Mullankandy, 2024).

5.4. Ethical AI Design in Advertising Algorithms

The design of AI algorithms must prioritize ethical considerations from inception through to deployment. This involves incorporating fairness metrics and bias mitigation strategies within the algorithmic design process (C. Singh, 2023). A commitment to ethical AI design encourages the development of algorithms that reflect equitable values and serve diverse audiences without perpetuating discriminatory practices (Adeyelu et al., 2024). Additionally, the ongoing assessment and improvement of these systems are essential to adapt to societal changes and emerging ethical standards (Xu et al., 2022). By embedding ethical principles into the core framework of AI advertising technologies, organizations can enhance their competitiveness while contributing positively to the societal impact of advertising practices (Mehrabi et al., 2019).

6. Final Thoughts and Suggestions for the Future

Through improvements in personalization, automation, and data-driven decision-making, advertising that is powered by artificial intelligence has significantly altered the state of the marketing landscape. But the rapid pace of its development has given rise to ethical concerns regarding the privacy of consumers, the bias of algorithms, the dissemination of false information, and transparency. To address these challenges, a balanced approach is required, one that makes use of the potential of artificial intelligence while also placing an emphasis on ethical standards and consumer trust.

Regulatory frameworks need to undergo evolution in order to provide more transparent guidelines for the responsible application of artificial intelligence in advertising. The incorporation of proactive bias mitigation strategies, stronger data protection mechanisms, and transparency in decision-making processes driven by artificial intelligence should be established as part of marketing practices. To ensure that the deployment of artificial intelligence is conducted in an ethical manner, it is necessary for policymakers, developers of AI, and marketers to work together across disciplines.

The long-term societal impact of artificial intelligence in advertising should be investigated in future research, with a particular focus on the impact it has on the autonomy and decision-making of consumers. In order to shape an advertising ecosystem that is both sustainable and responsible, it will be essential to develop artificial intelligence systems that are in accordance with ethical principles while maintaining efficiency.

References

Adebayo, A. A. (2024). Campaigning in the Age of AI: Ethical Dilemmas and Practical Solutions for the UK and US. *International Journal of Social Science and Human Research*, *07*(12). https://doi.org/10.47191/ijsshr/v7-i12-65

Adeyelu, O. O., Ugochukwu, C. E., & Shonibare, M. A. (2024). Automating Financial Regulatory Compliance With Ai: A Review and Application Scenarios. *Finance & Accounting Research Journal*, *6*(4), 580-601. https://doi.org/10.51594/farj.v6i4.1035

Aladeen, H. (2023). Investigating the Impact of Bias in Web Search Algorithms: Implications for Digital Inequality. https://doi.org/10.31219/osf.io/dmkar

Albaroudi, E., Mansouri, T., & Alameer, A. (2024). A Comprehensive Review of AI Techniques for Addressing Algorithmic Bias in Job Hiring. *Ai*, *5*(1), 383-404. https://doi.org/10.3390/ai5010019

Alenazi, S. A. (2015). The Effects of Statement Persuasiveness, Statement Strength, and Regulatory Focus on Manipulative Intent Inference. *Journal of Business & Economics Research (Jber)*, *13*(1), 43. https://doi.org/10.19030/jber.v13i1.9078

Ali, M., Sapie□y□ski, P., Korolova, A., Mislove, A., & Rieke, A. (2019). Ad Delivery Algorithms: The Hidden Arbiters of Political Messaging. https://doi.org/10.48550/arxiv.1912.04255

Altay, S., & Gilardi, F. (2024). People Are Skeptical of Headlines Labeled as AI-generated, Even if True or Human-Made, Because They Assume Full AI Automation. *Pnas Nexus*, *3*(10). https://doi.org/10.1093/pnasnexus/pgae403

An, Y., Chen, Y., & Li, S. (2021). Intention to Redeem M-Coupons and Intention to Disclose Personal Information: Based on Internet Using Motivation and M-Coupons Delivery Approach. 39-44. https://doi.org/10.1145/3507485.3507492

Andreou, A., Silva, M., Benevenuto, F. c., Goga, O., Loiseau, P., & Mislove, A. (2019). Measuring the Facebook Advertising Ecosystem. https://doi.org/10.14722/ndss.2019.23280

Arbaiza, F., Arias, J., & Robledo-Dioses, K. (2024). AI-Driven Advertising Activity: Perspectives From Peruvian Advertisers. *Communication & Society*, 273-292. https://doi.org/10.15581/003.37.4.273-292

Bellamy, R., Dey, K., Hind, M., Hoffman, S. C., Houde, S., Kannan, K., Lohia, P., Martino, J., Mehta, S., Mojsilović, A., Nagar, S., Ramamurthy, K. N., Richards, J. T., Saha, D., Sattigeri, P., Singh, M., Varshney, K. R., & Zhang, Y. (2019). AI Fairness 360: An Extensible Toolkit for Detecting and Mitigating Algorithmic Bias. *Ibm Journal of Research and Development*, *63*(4/5), 4:1-4:15. https://doi.org/10.1147/jrd.2019.2942287

Bhuiyan, M. S. (2024). The Role of AI-Enhanced Personalization in Customer Experiences. *Journal of Computer Science and Technology Studies*, *6*(1), 162-169. https://doi.org/10.32996/jcsts.2024.6.1.17

Camilleri, M. A. (2023). Artificial Intelligence Governance: Ethical Considerations and Implications for Social Responsibility. *Expert Systems*, *41*(7). https://doi.org/10.1111/exsy.13406

Camilleri, M. A. (2024). Artificial intelligence governance: Ethical considerations and implications for social responsibility. *Expert Systems*, *41*(7), e13406.

Cary, M. P., Bessias, S., McCall, J., Pencina, M., Grady, S. D., Lytle, K. S., & Economou-Zavlanos, N. (2024). Empowering Nurses to Champion Health Equity &Amp; BE FAIR: Bias Elimination for Fair and Responsible AI in Healthcare. *Journal of Nursing Scholarship*, *57*(1), 130-139. https://doi.org/10.1111/jnu.13007

Chang, Y.-L., & Ke, J. (2023). Socially Responsible Artificial Intelligence Empowered People Analytics: A Novel Framework Towards Sustainability. *Human Resource Development Review*, *23*(1), 88-120. https://doi.org/10.1177/15344843231200930

Cheong, J., Kuzucu, S., Kalkan, S., & Güneş, H. (2023). Towards Gender Fairness for Mental Health Prediction. 5932-5940. https://doi.org/10.24963/ijcai.2023/658

Chin, M. H., Afsarmanesh, N., Bierman, A. S., Chang, C., Colón-Rodríguez, C. J., Dullabh, P., Duran, D. G., Fair, M., Hernandez-Boussard, T., Hightower, M., Jain, A., Jordan, W. B., Konya, S., Moore, R. H., Moore, T. T., Rodriguez, R., Shaheen, G., Snyder, L. P., Srinivasan, M.,…Ohno-Machado, L. (2023). Guiding Principles to Address the Impact of Algorithm Bias on Racial and Ethnic Disparities in Health and Health Care. *Jama Network Open*, *6*(12), e2345050. https://doi.org/10.1001/jamanetworkopen.2023.45050

Chouaki, S., Bouzenia, I., Goga, O., & Roussillon, B. (2022). Exploring the Online Micro-Targeting Practices of Small, Medium, and Large Businesses. https://doi.org/10.48550/arxiv.2207.09286

Christanto, H. J., Dewi, C., Sutresno, S. A., & Silalahi, A. D. K. (2024). Analyzing the Use of Chat Generative Pre-Trained Transformer and Artificial Intelligence. *Revue D Intelligence Artificielle*, *38*(4), 1297-1304. https://doi.org/10.18280/ria.380423

Chu, C. H., Leslie, K., Shi, J., Nyrup, R., Bianchi, A., Khan, S. S., Rahimi, S. A., Lyn, A., & Grenier, A. (2022). Ageism and Artificial Intelligence:

Protocol for a Scoping Review. *Jmir Research Protocols*, *11*(6), e33211. https://doi.org/10.2196/33211

Corrêa, N. K., Galvão, C., Santos, J. W., Pino, C. D., Pinto, E. P., Barbosa, C., Massmann, D., Mambrini, R., Galvão, L., Terem, E., & Oliveira, N. d. (2023). Worldwide AI Ethics: A Review of 200 Guidelines and Recommendations for AI Governance. *Patterns*, *4*(10), 100857. https://doi.org/10.1016/j.patter.2023.100857

Cotter, K., Medeiros, M., Pak, C., & Thorson, K. (2021). "Reach the Right People": The Politics of "Interests" in Facebook's Classification System for Ad Targeting. *Big Data & Society*, *8*(1). https://doi.org/10.1177/2053951721996046

Drage, E., & Mackereth, K. (2022). Does AI Debias Recruitment? Race, Gender, and AI's "Eradication of Difference". *Philosophy & Technology*, *35*(4). https://doi.org/10.1007/s13347-022-00543-1

Egorenkov, D. (2022). AI-Powered Marketing Automation: Revolutionizing Campaign Management. *International Journal for Multidisciplinary Research*, *4*(2). https://doi.org/10.36948/ijfmr.2022.v04i02.23358

Elkhatat, A. M., Elsaid, K., & Al-Meer, S. (2023). Evaluating the Efficacy of AI Content Detection Tools in Differentiating Between Human and AI-generated Text. *International Journal for Educational Integrity*, *19*(1). https://doi.org/10.1007/s40979-023-00140-5

Eriksson, A. (2024). AI-Driven Advertising: Ethical Challenges, Frameworks, and Future Directions. https://doi.org/10.31219/osf.io/s8wbc

Fazil, A. W., Hakimi, M., & Shahidzay, A. K. (2023). A comprehensive review of bias in AI algorithms. *Nusantara Hasana Journal*, *3*(8), 1-11.

Fazil, A. W., Hakimi, M., & Shahidzay, A. K. (2024). A Comprehensive Review of Bias in Ai Algorithms. *Nusantara Hasana Journal*, *3*(8), 1-11. https://doi.org/10.59003/nhj.v3i8.1052

Ferrara, E. (2023). Fairness and Bias in Artificial Intelligence: A Brief Survey of Sources, Impacts, and Mitigation Strategies (Preprint). https://doi.org/10.2196/preprints.48399

Fletcher, R., Nakeshimana, A., & Olubeko, O. (2021). Addressing Fairness, Bias, and Appropriate Use of Artificial Intelligence and Machine Learning in Global Health. *Frontiers in Artificial Intelligence*, *3*. https://doi.org/10.3389/frai.2020.561802

Greguš, Ľ., & Škvareninová, S. (2023). Opinion Balance of News in the Time of Mistrust in Media and Democratic Institutions. 133-142. https://doi.org/10.34135/mmidentity-2023-13

Gupta, R., Srivastava, D., Sahu, M., Tiwari, S., Ambasta, R. K., & Kumar, P. (2021). Artificial Intelligence to Deep Learning: Machine Intelligence

Approach for Drug Discovery. *Molecular Diversity*, *25*(3), 1315-1360. https://doi.org/10.1007/s11030-021-10217-3

Hacker, P. (2021). Manipulation by Algorithms. Exploring the Triangle of Unfair Commercial Practice, Data Protection, and Privacy Law. *European Law Journal*, *29*(1-2), 142-175. https://doi.org/10.1111/eulj.12389

Heins, C. (2022). Artificial Intelligence in Retail – A Systematic Literature Review. *Foresight*, *25*(2), 264-286. https://doi.org/10.1108/fs-10-2021-0210

Hibbert, S., Smith, A., Davies, A., & Ireland, F. (2007). Guilt Appeals: Persuasion Knowledge and Charitable Giving. *Psychology and Marketing*, *24*(8), 723-742. https://doi.org/10.1002/mar.20181

Holloway, S. (2024). Exploring the Role of Digital Technologies in Enhancing Supply Chain Efficiency and Marketing Effectiveness. https://doi.org/10.20944/preprints202406.1538.v1

Howard, F. M., Li, A., Riffon, M., Garrett-Mayer, E., & Pearson, A. T. (2024). Characterizing the Increase in Artificial Intelligence Content Detection in Oncology Scientific Abstracts From 2021 to 2023. *Jco Clinical Cancer Informatics*(8). https://doi.org/10.1200/cci.24.00077

Hoxhaj, O., Halilaj, B., & Harizi, A. (2023). Ethical Implications and Human Rights Violations in the Age of Artificial Intelligence. *Balkan Social Science Review*, *22*(22), 153-171. https://doi.org/10.46763/bssr232222153h

Huang, Z., Chen, G., & Zhao, G. (2023). The Effect of Personalization on Consumer Behaviors. 389-405. https://doi.org/10.2991/978-94-6463-246-0_47

Huda, M., Awaludin, A., & Siregar, H. K. (2024). Legal Challenges in Regulating Artificial Intelligence: A Comparative Study of Privacy and Data Protection Laws. *Ijsh*, *1*(2), 116-125. https://doi.org/10.59613/g8dc9v94

Idoko, I. P., Igbede, M. A., Manuel, H. N. N., Adeoye, T. O., Akpa, F. A., & Ukaegbu, C. (2024). Big Data and AI in Employment: The Dual Challenge of Workforce Replacement and Protecting Customer Privacy in Biometric Data Usage. *Global Journal of Engineering and Technology Advances*, *19*(2), 089-106. https://doi.org/10.30574/gjeta.2024.19.2.0080

Illia, L., Colleoni, E., & Zyglidopoulos, S. C. (2022). Ethical Implications of Text Generation in the Age of Artificial Intelligence. *Business Ethics the Environment & Responsibility*, *32*(1), 201-210. https://doi.org/10.1111/beer.12479

Isaac, M. S., & Grayson, K. (2019). Priming Skepticism: Unintended Consequences of One-sided Persuasion Knowledge Access. *Psychology and Marketing*, *37*(3), 466-478. https://doi.org/10.1002/mar.21313

Jin, Y., & Skiera, B. (2022). How Do Privacy Laws Impact the Value for Advertisers, Publishers and Users in the Online Advertising Market? A Comparison of the EU, US and China. *Journal of Creating Value*, *8*(2), 306-327. https://doi.org/10.1177/23949643221117676

Jobin, A., Ienca, M., & Vayena, E. (2019). The Global Landscape of AI Ethics Guidelines. *Nature Machine Intelligence*, *1*(9), 389-399. https://doi.org/10.1038/s42256-019-0088-2

Khedekar, B., Shinde, S., Bagave, S., & Belvalkar, H. (2023). Beacon: The Desktop Voice Assistant. *International Research Journal of Modernization in Engineering Technology and Science*. https://doi.org/10.56726/irjmets35889

Khrais, L. T. (2020). Role of Artificial Intelligence in Shaping Consumer Demand in E-Commerce. *Future Internet*, *12*(12), 226. https://doi.org/10.3390/fi12120226

Kirmani, A., & Zhu, R. (2007). Vigilant Against Manipulation: The Effect of Regulatory Focus on the Use of Persuasion Knowledge. *Journal of Marketing Research*, *44*(4), 688-701. https://doi.org/10.1509/jmkr.44.4.688

Kish, K. (2020). Paying Attention: Big Data and Social Advertising as Barriers to Ecological Change. *Sustainability*, *12*(24), 10589. https://doi.org/10.3390/su122410589

Kokudeva, M., Vichev, M., Naseva, E., Miteva, D. G., & Velikova, T. (2024). Artificial Intelligence as a Tool in Drug Discovery and Development. *World Journal of Experimental Medicine*, *14*(3). https://doi.org/10.5493/wjem.v14.i3.96042

Kriaučiūnaitė-Lazauskienė, G. (2023). Grounded Theory in AI-enhanced Women's Image in Advertising. 228-240. https://doi.org/10.34135/mmidentity-2023-23

Kumar, D., & Suthar, N. (2024). Ethical and Legal Challenges of AI in Marketing: An Exploration of Solutions. *Journal of Information Communication and Ethics in Society*, *22*(1), 124-144. https://doi.org/10.1108/jices-05-2023-0068

Ledro, C., Nosella, A., & Vinelli, A. (2022). Artificial Intelligence in Customer Relationship Management: Literature Review and Future Research Directions. *Journal of Business and Industrial Marketing*, *37*(13), 48-63. https://doi.org/10.1108/jbim-07-2021-0332

Lim, D., Baek, T. H., Yoon, S., & Kim, Y. (2020). Colour Effects in Green Advertising. *International Journal of Consumer Studies*, *44*(6), 552-562. https://doi.org/10.1111/ijcs.12589

Liu, Z., Iqbal, U., & Saxena, N. (2024). Opted Out, Yet Tracked: Are Regulations Enough to Protect Your Privacy? *Proceedings on Privacy Enhancing Technologies*, *2024*(1), 280-299. https://doi.org/10.56553/popets-2024-0016

Lyndyuk, A., Havrylyuk, I., Tomashevskii, Y., Khirivskyi, R., & Kohut, M. (2024a). The impact of artificial intelligence on marketing communications: New business opportunities and challenges. *Economics of Development*, *4*(23), 60-71.

Lyndyuk, A., Havrylyuk, I., Tomashevskii, Y., Khirivskyi, R., & Kohut, M. (2024b). The Impact of Artificial Intelligence on Marketing Communications: New Business Opportunities and Challenges. *Economics of Development*, *23*(4), 60-71. https://doi.org/10.57111/econ/4.2024.60

Masood, M., Nawaz, M., Malik, K., Javed, A., Irtaza, A., & Malik, H. (2022). Deepfakes generation and detection: state-of-the-art, open challenges, countermeasures, and way forward. *Applied Intelligence*, *53*, 1-53. https://doi.org/10.1007/s10489-022-03766-z

Mehrabi, N., Morstatter, F., Saxena, N. A., Lerman, K., & Galstyan, A. (2019). A Survey on Bias and Fairness in Machine Learning. https://doi.org/10.48550/arxiv.1908.09635

Min, A. (2023). Artifical Intelligence and Bias: Challenges, Implications, and Remedies. *Journal of Social Research*, *2*(11), 3808-3817. https://doi.org/10.55324/josr.v2i11.1477

Mullankandy, S. (2024). Transforming Data Into Compliance: Harnessing AI/ML to Enhance Regulatory Reporting Processes. *Jaigs*, *3*(1), 62-73. https://doi.org/10.60087/jaigs.v3i1.66

Murdoch, B. (2021). Privacy and Artificial Intelligence: Challenges for Protecting Health Information in a New Era. *BMC Medical Ethics*, *22*(1). https://doi.org/10.1186/s12910-021-00687-3

Noranee, S., & Othman, A. K. (2023). Understanding Consumer Sentiments: Exploring the Role of Artificial Intelligence in Marketing. *Jmm17 Jurnal Ilmu Ekonomi Dan Manajemen*, *10*(1), 15-23. https://doi.org/10.30996/jmm17.v10i1.8690

Oh, H., Park, S., Lee, G. M., Heo, H., & Choi, J. K. (2019). Personal Data Trading Scheme for Data Brokers in IoT Data Marketplaces. *Ieee Access*, *7*, 40120-40132. https://doi.org/10.1109/access.2019.2904248

Osasona, F., Amoo, O. O., Atadoga, A., Abrahams, T. O., Farayola, O. A., & Ayinla, B. S. (2024). Reviewing the Ethical Implications of Ai in Decision Making Processes. *International Journal of Management & Entrepreneurship Research*, *6*(2), 322-335. https://doi.org/10.51594/ijmer.v6i2.773

Padmanaban, H. (2024). Revolutionizing Regulatory Reporting Through AI/ML: Approaches for Enhanced Compliance and Efficiency. *Jaigs*, *2*(1), 71-90. https://doi.org/10.60087/jaigs.v2i1.98

Park, H., Oh, H., & Choi, J. K. (2023). A Profit Maximization Model for Data Consumers With Data Providers' Incentives in Personal Data Trading Market. *Data*, *9*(1), 6. https://doi.org/10.3390/data9010006

Pawar, V., Patil, A., Tamboli, F. A., Gaikwad, D., Mali, D., & Shinde, A. J. (2023). Harnessing the Power of AI in Pharmacokinetics and Pharmacodynamics: A Comprehensive Review. *International Journal of Pharmaceutical Quality Assurance*, *14*(02), 426-439. https://doi.org/10.25258/ijpqa.14.2.31

Pizzi, G., Scarpi, D., & Pantano, E. (2021). Artificial Intelligence and the New Forms of Interaction: Who Has the Control When Interacting With a Chatbot? *Journal of Business Research*, *129*, 878-890. https://doi.org/10.1016/j.jbusres.2020.11.006

Pizzi, G., Vannucci, V., Mazzoli, V., & Donvito, R. (2023). I, Chatbot! The Impact of Anthropomorphism and Gaze Direction on Willingness to Disclose Personal Information and Behavioral Intentions. *Psychology and Marketing*, *40*(7), 1372-1387. https://doi.org/10.1002/mar.21813

Raji, M. A., Olodo, H. B., Oke, T. T., Addy, W. A., Ofodile, O. C., & Oyewole, A. T. (2024). E-Commerce and Consumer Behavior: A Review of AI-powered Personalization and Market Trends. *GSC Advanced Research and Reviews*, *18*(3), 066-077. https://doi.org/10.30574/gscarr.2024.18.3.0090

Reddy, S. V., Reddy, B., Dodda, S., Raparthi, M., & Maruthi, S. (2020). Ethical Considerations in AI-Enabled Big Data Research: Balancing Innovation and Privacy. https://doi.org/10.52783/ijca.v13i03.38350

Rosales, A., & Fernández-Ardèvol, M. (2019). Structural Ageism in Big Data Approaches. *Nordicom Review*, *40*(s1), 51-64. https://doi.org/10.2478/nor-2019-0013

Ryu, S. (2024). Brand Communications During a Global Crisis: Understanding Persuasion Intent, Perceived Brand Opportunism and Message Sincerity. *Journal of Product & Brand Management*, *33*(1), 162-178. https://doi.org/10.1108/jpbm-11-2022-4230

Sezgin, E., Huang, Y., Ramtekkar, U., & Lin, S. (2020). Readiness for Voice Assistants to Support Healthcare Delivery During a Health Crisis and Pandemic. *NPJ Digital Medicine*, *3*(1). https://doi.org/10.1038/s41746-020-00332-0

Sharma, S. (2023). Ethical Considerations in AI-Based Marketing: Balancing Profit and Consumer Trust. *TJJPT*, *44*(3), 1301-1309. https://doi.org/10.52783/tjjpt.v44.i3.474

Singh, C. (2023). Artificial Intelligence and Deep Learning: Considerations for Financial Institutions for Compliance With the Regulatory Burden in the United Kingdom. *Journal of Financial Crime*, *31*(2), 259-266. https://doi.org/10.1108/jfc-01-2023-0011

Singh, N. (2023). AI-Driven Personalization in eCommerce Advertising. *International Journal for Research in Applied Science and Engineering Technology*, *11*(12), 1692-1698. https://doi.org/10.22214/ijraset.2023.57695

Sodiya, E. O., Amoo, O. O., Umoga, U. J., & Atadoga, A. (2024). AI-driven Personalization in Web Content Delivery: A Comparative Study of User Engagement in the USA and the UK. *World Journal of Advanced Research and Reviews*, *21*(2), 887-902. https://doi.org/10.30574/wjarr.2024.21.2.0502

Sreerama, J., & Krishnamoorthy, G. (2022). Ethical Considerations in AI Addressing Bias and Fairness in Machine Learning Models. *Journal of Knowledge Learning and Science Technology Issn 2959-6386 (Online)*, *1*(1), 130-138. https://doi.org/10.60087/jklst.vol1.n1.p138

Sun, W., Nasraoui, O., & Shafto, P. (2020). Evolution and Impact of Bias in Human and Machine Learning Algorithm Interaction. *Plos One*, *15*(8), e0235502. https://doi.org/10.1371/journal.pone.0235502

Terzopoulos, G., & Satratzemi, M. (2020). Voice Assistants and Smart Speakers in Everyday Life and in Education. *Informatics in Education*, 473-490. https://doi.org/10.15388/infedu.2020.21

Tillu, R., Muthusubramanian, M., & Periyasamy, V. (2023a). From Data to Compliance: The Role of AI/ML in Optimizing Regulatory Reporting Processes. *Journal of Knowledge Learning and Science Technology Issn 2959-6386 (Online)*, *2*(3), 381-391. https://doi.org/10.60087/jklst.vol2.n3.p391

Tillu, R., Muthusubramanian, M., & Periyasamy, V. (2023b). Transforming Regulatory Reporting With AI/ML: Strategies for Compliance and Efficiency. *Journal of Knowledge Learning and Science Technology Issn 2959-6386 (Online)*, *2*(1), 145-157. https://doi.org/10.60087/jklst.vol2.n1.p157

Țîrcovnicu, G.-I., & Haţegan, C.-D. (2023). Integration of Artificial Intelligence in the Risk Management Process: An Analysis of Opportunities and Challenges. *Journal of Financial Studies*, *8*(15), 198-214. https://doi.org/10.55654/jfs.2023.8.15.13

Wasilewski, T., Kamysz, W., & Gębicki, J. (2024). AI-Assisted Detection of Biomarkers by Sensors and Biosensors for Early Diagnosis and Monitoring. *Biosensors*, *14*(7), 356. https://doi.org/10.3390/bios14070356

Weerarathna, I. N., Kamble, A. R., & Luharia, A. (2023). Artificial Intelligence Applications for Biomedical Cancer Research: A Review. *Cureus*. https://doi.org/10.7759/cureus.48307

Wiese, M., Martínez-Climent, C., & Botella-Carrubi, D. (2020). A Framework for Facebook Advertising Effectiveness: A Behavioral Perspective. *Journal of Business Research*, *109*, 76-87. https://doi.org/10.1016/j.jbusres.2019.11.041

Williamson, S., & Prybutok, V. R. (2024). Balancing Privacy and Progress: A Review of Privacy Challenges, Systemic Oversight, and Patient Perceptions in AI-Driven Healthcare. *Applied Sciences*, *14*(2), 675. https://doi.org/10.3390/app14020675

Xie, Y., & Huang, Y. (2023). A Novel Personalized Recommendation Model for Computing Advertising Based on User Acceptance Evaluation. *Ieee Access*, *11*, 140636-140645. https://doi.org/10.1109/access.2023.3339839

Xu, J., Xiao, Y., Wang, H., Ning, Y., Shenkman, E., Bian, J., & Wang, F. (2022). Algorithmic Fairness in Computational Medicine. https://doi.org/10.1101/2022.01.16.21267299

Xu, Y., Liu, Y., Wu, J., & Zhan, X. (2024). Privacy by Design in Machine Learning Data Collection: An Experiment on Enhancing User Experience. *Applied and Computational Engineering*, *97*(1), 64-68. https://doi.org/10.54254/2755-2721/97/20241388

Yadav, K., & Rathore, P. (2023). AI-Generated Content Detectors: Boon or Bane for Scientific Writing. *Indian Journal of Science and Technology*, *16*(39), 3435-3439. https://doi.org/10.17485/ijst/v16i39.1632

Yammouri, G., & Lahcen, A. A. (2024). AI-Reinforced Wearable Sensors and Intelligent Point-of-Care Tests. *Journal of Personalized Medicine*, *14*(11), 1088. https://doi.org/10.3390/jpm14111088

Zancan, C., Passador, J. L., & Passador, C. S. (2023). Integrating Python-Based Artificial Intelligence for Enhanced Management of Inter-Municipal Tourism Consortia: A Technological Approach. *Caderno Virtual De Turismo*, *23*(3), 83. https://doi.org/10.18472/cvt.23n3.2023.2103

Zhang, Y., & Gosline, R. (2023). Human Favoritism, Not AI Aversion: People's Perceptions (And Bias) Toward Generative AI, Human Experts, and Human–GAI Collaboration in Persuasive Content Generation. *Judgment and Decision Making*, *18*. https://doi.org/10.1017/jdm.2023.37

Zhao, H. (2024). Fair and Optimal Prediction via Post-processing. *Ai Magazine*, *45*(3), 411-418. https://doi.org/10.1002/aaai.12191

Ziakis, C., & Vlachopoulou, M. (2023). Artificial Intelligence in Digital Marketing: Insights From a Comprehensive Review. *Information*, *14*(12), 664. https://doi.org/10.3390/info14120664

Chapter 9

The Erosion of Consumer Autonomy

Canan Yılmaz Uz[1]

Seda Arslan[2]

Abstract

Consumer autonomy refers to an individual's capacity to make decisions independently, based on their own values, needs, and informed evaluations, free from external pressures. However, with digitalization, the use of big data, and marketing strategies driven by algorithms, this autonomy is increasingly eroding. Although today's consumers believe they are making conscious choices, they are, in fact, unbeware manipulated through personalized advertisements, AI-powered recommendation systems, and neuromarketing techniques. The erosion of consumer autonomy is not limited to advertising and marketing strategies but is also supported by algorithmic guidance, digital ecosystems that encourage constant consumption, and psychological manipulation tools. This phenomenon weakens consumers' ability to make rational decisions, promotes overconsumption, and fosters a sense of dissatisfaction.

This study aims to highlight the significance of consumer autonomy by examining its erosion process and its effects on consumer behavior. Furthermore, it discusses the disruptions in consumers' decision-making mechanisms, ethical concerns, and potential violations of consumer rights. The limited number of systematic studies on consumer autonomy in the literature emphasises the contribution of this research to the field and highlights the relevance of the topic within the dynamics of contemporary consumption.

1 Doç. Dr. İskenderun Teknik Üniversitesi, canan.yilmazuz@iste.edu.tr, https://orcid.org/0000-0002-4798-2262

2 Dr. Öğr. Üyesi, İskenderun Teknik Üniversitesi, seda.arslan@iste.edu.tr, https://orcid.org/0000-0002-8731-8294

https://doi.org/10.58830/ozgur.pub710.c3026

1. Introduction

In today's world, with the advancement of technology, the concept of consumption has undergone a significant transformation. Accordingly, consumer behavior has started to be shaped by various factors (Ertemel & Pektaş, 2018). This situation may also reduce consumers' ability to make autonomous choices (Sevastianova, 2023). Consumer autonomy refers to individuals' ability to access information and make free and informed choices (Wertenbroch et al., 2020). However, in the contemporary era, this freedom is increasingly eroded by various marketing strategies, algorithms, and manipulative consumption practices. The erosion of consumer autonomy is associated with the increasing presence of factors that hinder individuals from making independent decisions. In this context, the erosion of consumer autonomy can also occur through digital technologies, data-driven advertisements, and personalized marketing activities (Cunningham, 2003).

Before the Industrial Revolution, consumers had to choose from a small number of products and services. However, with technological advancements, the diversification of options and the provision of personalized experiences have enabled individuals to make choices aligned with their lifestyles. During this period of increasing technological advancements signifies an era that supports the increase in consumer autonomy. Nevertheless, in the digital age, consumer autonomy is increasingly challenged, as individuals are surrounded by manipulative practices that shape their free will. Particularly, technological advancements have transformed consumer behavior, and algorithm- and artificial intelligence-based systems now possess the ability to predict and influence individuals' preferences. This creates an environment highly susceptible to manipulation. The guidance of individuals in a setting where they do not make conscious decisions is not only an ethical concern but also a legal issue with significant implications. The erosion of consumer autonomy extends beyond an individual concern, beginning to impact the societal structure as well. The rapid expansion of the digital world may deepen social inequalities, and as manipulated consumers become more vulnerable, the foundations of a democratic consumer culture may be seriously threatened.

This book chapter aims to comprehensively examine the concept of consumer autonomy erosion, which has become a significant issue in consumer behavior in recent years. In the first section, the concept of autonomy is analyzed in detail, followed by an exploration of consumer autonomy and its erosion from various theoretical and practical perspectives.

Additionally, solutions to prevent the erosion of consumer autonomy are proposed, and legal, ethical, and strategic measures in this field are discussed.

2. The Concept of Autonomy

Autonomy is a state that nurtures individuals' desire to make choices and their sense of freedom (Bendapudi & Leone, 2003). This concept is associated with individuals' ability to make independent decisions. In the context of consumer behavior, autonomy can be defined as "the ability of consumers to make decisions and implement them independently, without external pressures and impositions" (Wertenbroch et al., 2020). Choices made by consumers with intrinsic motivation and conscious awareness constitute concrete examples of the autonomy experience, representing conditions where no constraints exist in the decision-making process, and free choice prevails (Andre et al., 2018; Aydın & Doğan, 2023).

Theoretically, the concept of autonomy can be linked to the Self-Determination Theory. According to the Self-Determination Theory (Deci & Ryan, 1985), humans are inherently predisposed to development, and their social environment significantly influences this process. Individuals' developmental trajectories are largely shaped and influenced by their surrounding environment. The intrinsic motivation for development, when combined with opportunities provided by environmental factors, forms the fundamental determinants of an individual's orientations and decision-making processes.

Sneddon (2001) categorizes autonomy into 'shallow autonomy' and 'deep autonomy.' Shallow autonomy refers to an individual's ability to freely choose among available options; however, this concept neglects the cognitive processes underlying an individual's choices and their connection to personal identity and values. At this level, individuals may make decisions based on external preferences but do not necessarily engage in deep contemplation or questioning of the values, desires, and personal identity underlying these decisions. Thus, while shallow autonomy offers superficial freedom of choice, it does not integrate the decision-making process with the individual's deeper psychological and philosophical dimensions.

Deep autonomy, in contrast, is more complex and multidimensional. This form of autonomy is not merely limited to the ability to make choices; rather, it requires individuals to develop deep intrinsic awareness regarding the values, goals, and identity that shape their choices, directing their lives accordingly. Deep autonomy involves a process in which individuals critically evaluate their beliefs, desires, and values. This process enables individuals to act with internal coherence, independent of external influences. Individuals do not simply make choices; they also question the alignment of these choices with their personal values and identity. As a result, deep autonomy transcends surface-level preferences, integrating decision-making with life goals, the search for meaning, and personal development. This process entails consciously reflecting on identity, values, and the meaning of life and incorporating these reflections into daily life practices. While shallow autonomy is limited to decision-making ability, deep autonomy involves questioning how one's choices align with personal identity and values and assessing the coherence of these choices (Schneider-Kamp & Askegaard, 2020). Shallow autonomy is confined to an individual's momentary decision-making ability, where choices are often not directly linked to personal identity and values. In contrast, deep autonomy requires individuals to move beyond decision-making and examine how their choices correspond with their values and long-term goals.

Schneider-Kamp & Askegaard (2020) emphasizes that deep autonomy does not disappear entirely. Individuals may occasionally make non-autonomous choices, be subjected to manipulation, experience external pressures, or make erroneous decisions. However, this does not eliminate their overall state of autonomy or indicate a loss of deep autonomy. Sneddon (2001) also asserts that external factors, such as advertising, pose a threat to deep autonomy. He argues that advertisements, by exerting a manipulative influence on individuals' values and choices, make decision-making more susceptible to external guidance. Shallow autonomy is restricted to an individual's ability to make immediate choices, often detached from personal identity and values. In contrast, deep autonomy requires individuals to not only make choices but also question the alignment of these choices with their values and long-term goals.

Sneddon (2011) highlights that deep autonomy is not entirely lost. Individuals may occasionally make non-autonomous choices, be subjected to manipulation, external pressures, or make erroneous decisions. However, this does not eradicate their overall autonomy or mean they have lost deep autonomy. Sneddon (2011) also notes that deep autonomy is particularly threatened by external factors such as advertising. External influences, including advertisements, can weaken individuals' free will by exerting a manipulative impact on their values and choices, making their decision-making process more susceptible to external direction. The application of deep autonomy involves two fundamental components:

- Evaluation of values: The individual questions the consistency between their values and their primary desires.

- Assessment of the desirability of values: The individual analyzes the extent to which their values are desirable or valid.

This process enables individuals to establish a stronger connection with their identity and values, fostering a deeper sense of self-awareness.

Autonomy is a multidimensional and interdisciplinary concept, examined from various perspectives in fields such as philosophy, psychology, sociology, and law. Each discipline analyzes autonomy through its own lens, discussing different aspects of the concept in diverse contexts. While this diversity allows for a deeper analysis of autonomy, it may also lead to misunderstandings when different conceptualizations of autonomy are used interchangeably across disciplines (Wertenbroch et al., 2020).

Philosophy is one of the disciplines that examines the concept of autonomy in the most profound manner, focusing on its relationship with free will. Free will refers to an individual's capacity to choose or reject a particular action. From this perspective, autonomy is related to an individual's ability to make decisions based on their free will, maintain control over their own life, and act according to their own values. Key philosophical questions include what free will is, how it functions, and under what conditions it is valid. These questions are central to ongoing, unresolved debates concerning the nature of free will (André et al., 2018).

For instance, Kane (2011) explains free will by arguing that individuals must have the capacity to "choose otherwise." This approach emphasizes not only the existence of choices but also the ability to make conscious and rational decisions among them. In contrast, Frankfurt (1971) examines free will from a more psychological perspective, focusing on an individual's "second-order desires." According to Frankfurt, a person's ability to regulate their first-order desires (such as physical or impulsive wants) is essential for autonomous will. This refers to an individual's capacity to control their own desires and act according to higher-order goals. This perspective encompasses not only immediate impulses but also the ability to act in alignment with long-term values and aspirations.

These philosophical discussions offer significant insights into understanding consumer behavior. In the modern consumption landscape, issues such as how individuals perceive their autonomy, the effects of marketing strategies on these perceptions, and whether consumers can make fully informed decisions are directly related to these philosophical debates.

Consumer autonomy should be examined not only in terms of individual preferences and freedom of will but also within the framework of the social and economic structures that influence individuals. Therefore, incorporating philosophical analyses into studies on consumer autonomy can facilitate an interdisciplinary understanding and contribute to a more comprehensive exploration of the various dimensions of autonomy.

3. Consumer Autonomy

Consumer autonomy refers to the ability of individuals to make consumption decisions independently and with minimal external influence. As Bauman (1988) stated, consumer autonomy does not necessarily imply strong self-determination or complete independence of individual will; however, it delineates highly valuable boundaries for consumers. These boundaries serve to protect consumers from the exploitation of powerful corporations, misleading advertisements, coercion, and other unfair practices (Bauman, 1988). Autonomous consumer choice refers to a self-determined and independent decision-making process whereby an individual makes purchasing decisions—whether to buy or not buy certain products—based on their own will. This choice is entirely driven by the individual's personal beliefs and desires and is thus genuinely personal (Siipi & Uusitalo, 2008; Zhu, et al., 2024).

For a consumer's choices to be autonomous, three fundamental conditions must be met. First, the consumer must possess competence. Second, the consumer must have genuine desires and beliefs. Third, the consumer must have the capacity to apply these beliefs and desires to their choices (Raikka, 1999; Beauchamp, 2005). Consumer competence refers to having the necessary psychological and physical capacities for self-determination and autonomous decision-making. This capacity encompasses the ability to form beliefs and determine desires (Raikka, 1999; Pietarinen, 1994; Hyun, 2001; Oshana, 1998). The second condition for choice autonomy is that the consumer's beliefs and desires must be genuine and authentic to them. For a consumer's beliefs and desires to be considered authentic, they must be free from coercion or constraints. In other words, authentic desires and beliefs emerge without manipulation or excessive external influence (Hyun, 2001; Beauchamp & Childress, 2001). The third condition for autonomy in decision-making is that the individual must have the capacity to act upon their beliefs and desires. A person with this capacity not only holds authentic beliefs and desires but is also able to make decisions based on them. That is, the consumer can determine what to choose based on their own beliefs and desires (Streiffer & Rubel, 2004; Oshana, 1998). The ability to make a choice requires the existence of multiple alternatives; at the very least, the individual must believe that alternatives are available. If no alternatives exist, the individual cannot make a choice. Consequently, if a person is unable to make a choice, their choices cannot be considered autonomous (Siipi & Uusitalo, 2011).

Autonomy does not require consumers to be completely shielded from persuasive marketing strategies. Instead, autonomy focuses on ensuring that consumers have a fair opportunity to make informed and free decisions when exposed to persuasive marketing tactics, without feeling coerced, deceived, or misled. This entails that consumers should be able to make choices based on their own desires and needs, free from external pressures or misleading influences (Anker, 2020). In its classical sense, autonomy refers to an individual's capacity for self-governance, independent of external control or manipulation, emphasizing independence. The marketing literature plays a crucial role in conceptualizing consumer autonomy. However, as observed in European Union regulations, the concept of autonomy has not been adequately addressed in marketing ethics. Literature reviews on the subject reveal that autonomy is generally defined as a concept encompassing control, will, desire, choice, and self-reflection. Consumers are often not sufficiently motivated to actively seek or engage with important product information (Bakos et al., 2014). This presents a significant issue: across the European Union, 24% of consumers never read contract terms and conditions, while 36% only partially read them (Eurobarometer, 2011). A recent study found that out of 1,000 retail software purchasers, only one or two thoroughly reviewed the licensing agreements, and most of those who did only read a small portion (Bakos et al., 2014).

To understand the extent of information deficiency in consumer decision-making processes, one must consider the critical point that terms and conditions contain legally mandated information that sellers are required to provide to consumers. However, the ineffectiveness of such information stems from businesses overwhelming consumers with excessive data, rendering the information unprocessable. This phenomenon, referred to as "data dumping," significantly weakens consumers' ability to make autonomous decisions when faced with an overload of textual information (Zhu et al., 2024). Decision uncertainty points to fundamental ambiguities affecting an individual's autonomy, which complicate independent and informed decision-making processes (Schneider-Kamp & Askegaard, 2020).

Consumer autonomy is influenced not only by the decisions consumers make based on their own preferences and capacities but also by businesses' marketing communication efforts and the actions and regulations of other market actors (Hyman et al., 2023). Moreover, consumer autonomy is directly linked to both internal (e.g., cognitive and volitional capacities) and external factors (e.g., access to information and epistemic market conditions such as consumer rights). In this context, decision-making processes that impact consumer autonomy are shaped by the interaction between individual capacity and environmental conditions. More importantly, consumer autonomy is considered a critical prerequisite for legitimizing marketing as a social system on an ethical foundation in capitalist societies (Fassiaux, 2023). In light of existing research in marketing theory, Anker (2024) examines consumer autonomy within the framework of internal and external conditions. According to Anker, when consumers have access to the information they need and possess the capacity for critical thinking aligned with their values and goals, their level of autonomy increases. However, it is widely accepted that consumer autonomy is also significantly influenced by cognitive limitations and social contexts.

In the context of consumer autonomy, the need for autonomy pertains to individuals' sense of being able to make their own decisions independently, enabling them to take an autonomous role in consumption decisions (Gümüş & Gegez, 2017). Protecting consumer autonomy requires careful consideration of the distinction between autonomy and the preservation of informed choices. Autonomy does not imply completely isolating consumers from marketing influences; rather, it seeks to ensure that individuals exposed to marketing messages can make conscious, freely determined decisions without being manipulated, misled, or deprived of crucial information. Anker (2020) defines the protection of consumer autonomy as the establishment of an environment where consumers can make informed and free choices. In this regard, preventing manipulative or coercive strategies and ensuring that consumers receive transparent and accurate information are of paramount importance.

4. The Erosion of Consumer Autonomy

Discussions on the erosion of consumer autonomy, where consumers' freedom of choice is subject to various external interventions and restrictions, are increasingly gaining attention (Hyman et al., 2023). The erosion of autonomy pertains to the growing influence of external factors (such as marketing, social pressures, and digital algorithms) on consumer decisions. A consumer whose autonomy is limited finds their choices significantly shaped by external interventions, or their ability to negotiate or act in accordance with their desires and beliefs is hindered by mental or physical barriers (Siipi & Uusitalo, 2011).

The ability of consumers to make autonomous decisions enables the legitimacy of marketing as a social practice within capitalist economies (Cluley, 2019; Villarán, 2017). Marketing can be defined as a social system shaped by the exchange of goods or services between providers and consumers (Lusch & Watts, 2018; Lüedicke, 2006; Anderson et al., 1999; Bagozzi, 1975; Houston & Gassenheimer, 1987). The ethical validity of these exchanges is ensured when all parties consciously and voluntarily accept the exchange (Brenkert, 2008; Caruana et al., 2008; Nixon & Gabriel, 2016). However, many consumers report encountering incomplete and misleading information, which weakens their ability to make informed decisions and act autonomously (EC, 2015; Eurobarometer, 2011). The lack of consumer information is not limited to situations where fairness is absent; it can also be observed even where proper regulations exist. This issue arises due to consumers' difficulty in accessing information, the complexity of product and service structures, or the influence of marketing strategies. Some external factors have been identified in the EU "Unfair Commercial Practices Directive" (EUR-LEX, 2005) as having the potential to threaten personal autonomy through elements such as harassment and coercion. This raises a crucial question: what are the distinctions between external influences that threaten autonomy and those that align with it? In this context, the debate on autonomy gains significant importance in terms of marketing ethics. For instance, impulsive buying is a frequently encountered consumer behavior that illustrates the conflict between autonomy and marketing (Chan et al., 2017; Moser, 2018; Strack et al., 2006). Previous studies have supported the strong relationship between impulsive buying and the purchase of undesirable products, often leading to consumer regret (Hoch & Loewenstein, 1991; Lee et al., 2015; Wood, 1998). This finding can be considered a significant indicator of violations of consumer autonomy.

The concept of consumer autonomy offers a perspective that examines the impact of marketing methods and practices on individuals' independent decision-making processes and the extent to which they align with these processes (e.g., Anker et al., 2010; Arrington, 1982; Barrett, 2000; Bishop, 2000; Crisp, 1987; Cunningham, 2003; Raley, 2006; Sneddon, 2001; Villarán, 2017). Factors contributing to the erosion of autonomy include targeted advertisements, social media algorithms, pricing strategies, psychological interactions, and recommendation systems. These factors can hinder consumers' ability to make informed decisions. Research on consumer psychology suggests that impulsive buying has a psychological explanation within the context of self-regulation and self-control deficiencies (Chen & Wang, 2016; Verplanken & Sato, 2011; Yi & Baumgartner, 2011). In this regard, impulsive buying emerges as a prevalent consumer behavior that significantly weakens autonomy due to marketing strategies (Baumeister, 2002). Consequently, impulsive purchasing behaviors result from external marketing factors manipulating consumer decisions and restricting their free will.

Persuasive marketing strategies play a complex role in the erosion of consumer autonomy. These strategies do not always pose a threat to autonomy; on the contrary, they can serve as an essential tool in constructing brand identities and symbolic values. For example, brands such as Nike in sportswear or Apple in technology invest heavily in marketing strategies to enhance the symbolic meanings of their products. Such strategies encourage consumers to identify with products and develop brand loyalty. In this context, consumer exposure to persuasive marketing messages can sometimes be seen not as an interference with autonomy but as a means of expressing individual preferences. However, a critical distinction must be made: while persuasive marketing provides consumers with options and supports their capacity to make informed choices, it also carries the risk of eroding autonomy through manipulative and misleading tactics.

4.1. Ethical Perspectives: The Erosion of Consumer Autonomy

The marketing discipline has often been criticized for violating consumer autonomy (Hackley, 2009). Consumers value the ability to choose products and services that align with their personal preferences as an essential aspect of autonomy (Anker, 2020). However, marketers' infringement on this autonomy raises ethical concerns. For instance:

- Violations of ethical transparency principles,

- Disrespect for consumer dignity and rights,

- Encouragement of the consumption of products that disregard environmental sustainability.

Such instances give rise to serious ethical concerns regarding autonomy. The various methods used by marketing professionals to influence consumers' decision-making processes highlight the central role of autonomy in marketing ethics (Anker, 2020; Arrington, 1982; Crisp, 1987; Sunstein, 2016; Thaler & Sunstein, 2009). This underscores that the preservation of consumer autonomy is not only a matter of individual preferences but also a critical aspect of the ethical dimension of marketing.

Western Enlightenment thought regards individual free will and autonomy as fundamental values. This understanding has been linked to economic theories concerning consumers' capacity for free choice. Consumers exercise their autonomy by freely selecting from available options. However, this autonomy is constrained by factors such as freedom, price, time, and lack of information. Consumer behavior research has extensively examined consumers' efforts to overcome these limitations (Wertenbroch et al., 2020). The erosion of consumer autonomy is a significant ethical issue, closely associated with concepts such as consumer rights, information privacy, and the fight against manipulation. More than one-third of consumers in the European Union report feeling uninformed and unaware (Eurobarometer, 2011), and a substantial proportion lacks sufficient knowledge about fundamental consumer rights (EC, 2015). These informational deficiencies hinder consumers' ability to exercise their autonomy effectively and make informed decisions. In this context, marketing strategies and advertisements may pose a threat to consumer autonomy, as they have the potential to manipulate and mislead individuals.

According to the Kantian perspective, the actions of individuals lacking autonomy are not ethically assessable. Kant (1999) argues that an individual's capacity to make decisions regarding their own actions is inherently linked to moral responsibility. In this regard, autonomy is considered an ethical responsibility. However, in contemporary society, particularly with the rise of digital marketing and data-driven advertising, safeguarding consumer autonomy has become increasingly complex. Pragmatist philosophers, on the other hand, associate autonomy with ethical responsibility and emphasize that for an individual to act with free will, others must respect their autonomy (Hyman et al., 2023). This perspective frames autonomy as an interdependent component of individual freedom and responsibility. Thus, adopting a philosophical approach to understanding consumer behavior is crucial when examining the effects of marketing strategies and their potential interference in individuals' decision-making processes.

Consumer autonomy should not be viewed solely through the lens of individual preferences but rather within a broader framework shaped by social and economic structures. In the modern consumer landscape, the digitalization and personalization of marketing strategies may significantly erode consumer autonomy. Specifically, algorithms, artificial intelligence, and data-driven marketing techniques can obstruct consumers from making conscious choices. This situation underscores the need to redefine ethical boundaries to ensure the protection of consumer autonomy. From an ethical standpoint, consumers should be provided with transparent, accurate, and comprehensive information, allowing them to make choices free from manipulation.

Modern digital environments contain significant elements that threaten consumer autonomy. For instance, tracking personal data and utilizing it to deliver personalized offers may constitute a violation of individual privacy. The collection, use, and sharing of personal data often occur without consumer consent or awareness. Ethically, such data usage should be entirely transparent and based on consumer approval. This suggests that preserving consumer autonomy is not only contingent upon corporate transparency but also on enhancing consumers' digital literacy, enabling them to make informed choices. Consumer autonomy is threatened not only by manipulation and deception but also by issues such as lack of information, power imbalances, and privacy violations. The loss of consumer autonomy represents a profound ethical issue, and addressing this challenge necessitates the implementation of fairer, more transparent, and more conscientious marketing strategies. Ethical responsibility requires both governments and corporations to address these issues and take stronger steps toward safeguarding consumer autonomy.

4.2. Consumer Autonomy in the Digital World and the Erosion of Consumer Autonomy

In digital platforms, particularly in areas such as e-commerce and social media, the collection of personal data and the presentation of customized content based on this data have the potential to influence consumer preferences. Online consumers navigate increasingly complex and information-dense environments in their decision-making processes. However, these environments do not only weaken consumers' ability to make choices—and thus their autonomy—due to information overload and cognitive stress; the deliberate manipulation strategies employed by digital platforms further complicate this process (Mik, 2016).

In the modern consumer world, the nature of marketing strategies includes numerous elements that may contribute to the erosion of consumer autonomy. Cunningham (2003) asserts that a marketer cannot force consumers to accept existing attitudes or change their preferences. However, the rise of digital technologies and data-driven advertising has increasingly blurred these boundaries. Algorithms and personalized marketing techniques not only predict consumer preferences but also develop strategies to shape them. Rather than supporting consumer autonomy, this situation holds the potential to erode it. Consumers may believe they are making choices in line with their own desires, yet due to the manipulations and directives they are exposed to, they may unknowingly be steered toward certain preferences. Even if a consumer initially has no interest in a product, continuous exposure to advertisements and algorithmic recommendations may direct them toward it. From this perspective, it can be argued that consumers do not always engage in rational decision-making but rather act within the alternatives presented to them. Consumers guided in this manner inadvertently become trapped in specific consumption patterns, further restricting their ability to make conscious choices. In this context, the question arises as to whether personalized marketing truly serves the interests of consumers.

Marketing researchers study how consumers perceive the digital ecosystem and how they behave within it. While artificial intelligence (AI) provides significant advantages to consumers, research suggests that the growing influence of AI and machine learning tools, along with the increasing dominance of online platforms, threatens consumer freedom of choice and personal autonomy. In particular, the delegation of decision-making processes to AI has led to the emergence of a phenomenon known in the literature as "modified consumers." This concept implies that choices in the shopping process are no longer entirely under individual control, and consumption preferences play a diminishing role in identity formation through conscious decisions and personal effort (Sevastianova, 2023). Although AI and machine learning technologies facilitate consumer decision-making processes, they simultaneously threaten consumer autonomy. By predicting consumer decisions based on past data, these technologies may limit the ability to make free choices, thereby creating a "lock-in effect." For instance, even if a consumer wishes to adopt a healthier lifestyle, AI may recommend unhealthy products based on past purchasing habits. Additionally, AI-generated recommendations do not offer consumers opportunities for negotiation or alternative choices, leading to the erosion of autonomy. In the long run, this process may result in consumers losing their ability to engage in independent thought and decision-making. The weakening of choice and autonomy may cause consumers to make less relevant decisions, develop hostility toward new technologies, or experience a sense of learned helplessness. These reactions negatively impact consumers' ability to make independent choices and further diminish their autonomy.

The impact of AI and machine learning tools on consumer autonomy varies depending on the degree to which consumer decisions are linked to personal identity. If a consumer bases decisions on personal identity, values, or lifestyle, AI-generated recommendations may significantly undermine autonomy. Additionally, cultural and individual differences must be considered. Consumers' trust in AI—particularly in human-like technologies such as voice assistants and robots—plays a crucial role. The constraints imposed by these tools on choice and autonomy influence how consumers respond to such limitations; some consumers may react more strongly to these restrictions (Sevastianova, 2023).

Law literature frequently associates AI advancements with concerns about technological dominance, where computers exert control over humans. However, these concerns are often dismissed as exaggerated predictions, overlooking the fundamental issue at hand. The core problem lies not in technology serving as a mere tool but in its facilitation of power imbalances, allowing certain actors to gain dominance over others. In the context of online commerce, some entities have the potential to exert control over their counterparts, reinforcing asymmetries in access to information and power. In this regard, the growing control of specific actors over information and power through technology leads to the erosion of consumer autonomy (Pasquale, 2007). This poses a critical issue that should not be overlooked. With the proliferation of online commerce, consumer decisions now encompass not only simple choices—such as purchasing books or electronic devices—but also high-risk and complex financial transactions. The digital mediation of decisions regarding insurance plans and financial products increases the risk of consumers being influenced by technological guidance. It is crucial to highlight that the issue is not merely about temporary consumer frustrations stemming from paying higher prices for certain products. The fundamental concern is that technological guidance directly affects individuals' capacity for conscious and autonomous decision-making, systematically shaping their choices. This demonstrates that consumer autonomy is being significantly eroded and that the manipulative potential of digital environments is becoming an increasingly serious threat.

The erosion of consumer autonomy has become a significant dimension of the dynamics of online commerce. Online environments, mediated by technology, present various factors that directly influence consumer decision-making processes. Manipulated information inherent in online commerce weakens consumer autonomy. A consumer, expected to make informed decisions, becomes dependent on algorithmically driven and marketing-influenced content. The way consumers perceive online marketplaces and products is largely shaped by the strategies employed by online businesses. The design of online businesses is a deliberate effort to influence consumer behavior. The prioritization of certain content while making other content less accessible restricts consumer choices, thereby weakening their autonomous decision-making abilities. Consumers make decisions based solely on the options presented to them, encountering difficulties in accessing alternatives and comprehensive information (De Mul and Van Den, 2011). Notably, consumer attention is becoming an increasingly scarce resource in digital environments. Digital platforms employ various strategies to direct consumers' limited attention toward specific products or services, leading to decisions influenced by external factors rather than independent reasoning. As a result, consumers' ability to think independently and make autonomous choices diminishes, as external influences frequently intervene in their decision-making processes. The strategies employed in online commerce and digital marketing create an environment that erodes consumer autonomy. The exposure of consumers to a limited range of content restricts their decision-making processes, ultimately leading to the loss of individual autonomy. In the long term, this may result in consumer behavior becoming more predictable and controllable (Wertheimer, 2014).

Initially, technology is often employed to "optimize user experience" or to create "frictionless transaction processes." However, it is frequently overlooked that these optimizations primarily serve businesses rather than consumers. In theory, digital environments are expected to provide consumers with more choices, greater information access, and lower prices. In practice, however, these environments tend to limit choices, restrict access to information, and reduce consumer surplus. Online businesses influence consumer behavior through various technological interventions that determine how and when information is presented. This results in an unprecedented power imbalance between the parties involved in transactions, raising significant concerns not only about the extent of procedural exploitation permitted by contract law and the adequacy of existing consumer protection regulations but also about the broader impact of technology on consumer autonomy. Ultimately, technology is never neutral: Depending on how it is utilized, it may either preserve and enhance consumer autonomy by strengthening the ability to make informed choices or restrict autonomy by imposing externally dictated preferences (Mik, 2016).

5. Conclusion

The preservation of consumer autonomy necessitates the redefinition of the ethical boundaries of persuasive marketing strategies. Creating a consumer environment in which individuals are fully informed, their choices remain independent of manipulative influences, and they can make decisions of their own free will emerges as a critical requirement from both an ethical perspective and the standpoint of long-term sustainability. In this regard, the erosion of consumer autonomy should be considered not only as a matter of individual freedom but also as a fundamental issue affecting the democratic consumer culture.

In the past, technology was merely a tool used to achieve specific goals and objectives; however, today, it has transcended this role, evolving into a mechanism that grants certain actors access to information and power. This transfer of power provides businesses and digital platforms with data that influence consumer preferences, enabling them to utilize this information in line with their own interests. It is evident that the power conferred by technology is not always distributed equally and fairly, resulting in a pronounced power asymmetry among various stakeholders. This imbalance allows certain actors to exert a greater influence on consumers. Consequently, rather than making conscious and independent choices, consumers exposed to such mechanisms tend to act according to external directives shaped by these influences. By collecting consumer data and analyzing behavioral patterns, these actors can predict future consumer actions, thereby guiding and manipulating decision-making processes. Consumers subjected to such manipulation—whether consciously or unconsciously—experience a weakening of their free will, and their capacity for independent decision-making is significantly eroded. The resulting asymmetrical power structure hinders consumers from making choices based on their own preferences and aligning their decisions with their individual needs and desires. Data-driven algorithms and targeted personalized advertisements restrict the number and diversity of options available for consideration, thereby shaping decision-making processes. Consequently, consumers' ability to make informed and autonomous choices is progressively weakened.

Consumer autonomy ensures that individuals can make conscious and independent decisions based on their personal motivations and needs, thereby strengthening their ability to accept or reject marketing offers (Brenkert, 2008). This concept also holds a significant position in European Union consumer law. Specifically, under the Unfair Commercial Practices Directive (EUR-LEX, 2005), a commercial practice may be deemed unfair if it significantly impairs, or has the potential to impair, the freedom of choice or decision-making of the average consumer regarding a product and if such an impairment results in, or is likely to result in, a transactional decision that the consumer would not otherwise have made. This regulation aims to protect consumer autonomy and ensure that consumers can make decisions freely, without being subject to manipulative influences. In this context, safeguarding consumer rights, implementing fair marketing strategies, and preventing consumers from being rendered vulnerable to manipulation must be reinforced through legal regulations and strategic policies. Preventing the erosion of consumer autonomy requires a strong focus on the effectiveness of legal measures and consumer protection policies in this domain. Defining ethical and legal boundaries in marketing necessitates an approach that supports fair and informed decision-making processes while safeguarding consumer autonomy from potential threats.

References

Anderson, W.T., Challagalla, G.N., & McFarland, R.G. (1999). Anatomy of exchange. *Journal of Marketing Theory and Practice*, *7*(4), 8–19.

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D. H., Goldstein, W., Huber, J. C., van Boven, L., Weber, B., & Yang, H. (2018). Consumer choice and autonomy in the age of artificial ıntelligence and big data. *Customer Needs and Solutions, 5*(1-2), 28–37.

Anker, T. B. (2024). Meaningful choice: Existential consumer theory. *Marketing Theory*, *24*(4), 591-609.

Anker, T. (2020). Autonomy as license to operate: Establishing the internal and external conditions of informed choice in marketing. *Marketing Theory, 20*(4), 527-545.

Anker, T.B., Kappel, K., & Sandøe, P. (2010). The liberating power of commercial marketing, *Journal of Business Ethics*, *93*(4), 519–30.

Arrington, R.L. (1982). Advertising and behaviour control. *Journal of Business Ethic*s *1*(1), 3-12.

Aydın, A. E. & Dogan, V. (2023). Kriz ortamında tüketici ataleti: Whatsapp kişisel veri düzenlemesi üzerine bir araştırma. *Pazarlama ve Pazarlama Araştırmaları Dergisi*, *16*(1), 61-82.

Bagozzi, R.P. (1975). Marketing as exchange. *Journal of Marketing, 39*(4), 32-39.

Bakos, Y., Marotta-Wurgler, F., & Trossen, D.R. (2014). Does anyone read the fine print? Consumer attention to standard-form contracts. *Journal of Legal Studies 43*(1), 1–35.

Barrett, R. (2000). Market arguments and autonomy. *Journal of Philosophy of Education 34*(2), 327–341.

Bauman, Z. (1988). *Freedom*. Open University Press.

Baumeister, R.F. (2002). Yielding to temptation: Self-control failure, impulsive purchasing, and consumer behavior. *Journal of Consumer Research*, *28*(4), 670–676.

Bendapudi, N. & Leone, R. P. (2003). Psychological implications of customer participation in co-production. *Journal of Marketing, 67*(1), 14–28.

Bishop, J.D. (2000). Is self-identity image advertising ethical? *Business Ethics Quarterly, 10*(2), 371–398.

Brenkert, G. (2008). *Marketing ethics*. Blackwell Publishing.

Caruana, R. & Crane, A. (2008). Constructing consumer responsibility: Exploring the role of corporate communications. *Organization Studies, 29*(12), 1495–1519.

Chan, T.K.H., Cheung, C.M.K. & Lee, Z.W.Y. (2017). The state of online impulse-buying research: A literature analysis. *Information & Management 54*(2), 204–217.

Chen, Y.F. & Wang, R.Y. (2016). Are humans rational? Exploring factors influencing impulse buying intention and continuous impulse buying intention. *Journal of Consumer Behaviour, 15*(2), 186–97.

Cluley, R. (2019). The politics of consumer data. *Marketing Theory, 20*(1), 45–63.

Crisp, R. (1987). Persuasive advertising, autonomy, and the creation of desire. *Journal of Business Ethics, 6*(5), 413-418.

Cunningham, A. (2003). Autonomous consumption: Buying into the ideology of capitalism. *Journal of Business Ethics, 48*(3), 229–236.

Deci, E. L. & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior.* Plenum.

De Mul, J., & van den Berg, B. (2011). Remote control: Human Autonomy in the Age of Computer-Mediated Agency. In Law, Human Agency and Autonomic Computing (pp. 46-63). Routledge.

EC (European Commission) (2015). Consumer Conditions Scoreboard: Consumer at Home in the Single Market. URL (consulted 7 June 2019): https://ec.europa.eu/info/publications/consumer-conditionsscoreboard-consumers-home-single-market-2015-edition_en.

Ertemel, A. V. & Pektaş, G. Ö. E. (2018). Dijitalleşen dünyada tüketici davranışları açısından mobil teknoloji bağımlılığı: Üniversite öğrencileri üzerine nitel bir araştırma. *Yıldız Sosyal Bilimler Enstitüsü Dergisi*, *2*(2), 18-34.

EUR-LEX (2005). Directive 2005/29/EC of the European Parliament and of the Council of 11 May 2005 Concerning Unfair Business-to-Consumer Commercial Practices in the Internal Market (Unfair Commercial Practices Directive). URL (consulted 7 June 2019): https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri¼OJ:L:2005:149:0022:0039:en:PDF.

Eurobarometer (2011). Consumer Empowerment, TNS Opinion & Social, Special Eurobarometer 342/Wave 73.2 and 73.3. Survey requested by Eurostat and the Directorate-General for "Health and Consumers" (DG SANCO) and coordinated by the Directorate-General for Communication.

Fassiaux, S. (2023). Preserving consumer autonomy through European Union regulation of artificial intelligence: A long-term approach. *European Journal of Risk Regulation, 14*(4), 710-730.

Frankfurt, H.G. (1971). Freedom of the will and the concept of a person. *Journal of Philosophy, 68*(1), 5-20.

Gümüş, B. & Gegez, E. E. (2017). Değişen tüketici kültüründe yeni trend: Ortak tüketim. *Pazarlama ve Pazarlama Araştırmaları Dergisi*, *10*(20), 155-178.

Hackley, C. (2009). *Marketing: A critical introduction*. Sage Publications Inc.

Hoch, J.S. & Loewenstein, G.F. (1991). Time-inconsistent preferences and consumer self-control, *Journal of Consumer Research 17*(4), 492–507.

Houston, F.S. & Gassenheimer, J.B. (1987). Marketing and exchange, *Journal of Marketing, 51*(4), 3–18.

Hyman, M. R., Kostyk, A. & Trafimow, D. (2023). True consumer autonomy: A formalization and implications. *Journal of Business Ethics*, *183*(3), 841-863.

Hyun, I. (2001). Authentic values and individual autonomy. *Journal of Value Inquiry, 35*, 195–208.

Kane, R. (2011). *The Oxford handbook of free will.* New York: Oxford University Press.

Kant, I. (1999). *The Cambridge edition of the works of Immanuel Kant: Practical philosophy*. Cambridge University Press.

Lee, L., Lee, M. P., Bertini, M., Zauberman, G., & Ariely, D. (2015). Money, time, and the stability of consumer preferences. *Journal of Marketing Research*, *52*(2), 184-199.

Lusch, R.F. & Watts, J.K.M. (2018). Redefining the market: A Treatise on exchange and shared understanding. *Marketing Theory, 18*(4), 435–449.

Lüdicke, M. K. (2006). *A theory of marketing: Outline of a social systems perspective.* Deutscher Universitäts-Verlag.

Mik, E. (2016). The erosion of autonomy in online consumer transactions. *Law, Innovation and Technology*, *8*(1), 1-38.

Moser, C. (2018). Impulse buying: Interventions to support self-control with e-commerce'. *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems, Canada*, 1 – 4. https://doi.org/10.1145/3170427.3173026

Nixon, E. & Gabriel, Y. (2016). So much choice and no choice at all: A socio-psychoanalytic interpretation of consumerism as a source of pollution. *Marketing Theory 16*(1), 39–56.

Oshana, M. (1998). Personal autonomy and society. *Journal of Social Philosophy, 29*(1), 81–102.

Pasquale, F. (2007). Technology, competition, and values. Minn. JL Sci. & Tech., 8, 607.

Pietarinen, J. (1994). Itsemääräämінen ja itsemääräämisoikeus. In J. Pietarinen, V. Launis, J. Räikkä, E. Lagerspetz, M. Rauhala & M. Oksanen (Eds.), *Oikeus itsemääräämiseen* (pp., 15-47). Painatuskeskus.

Räikkä, J. (1999). On morality of avoiding information. In V. Launis, J. Pietarinen, & J. Räikkä (Eds.), Genes and morality (pp. 63–75). Rodopi.

Raley, Y. (2006). Food advertising, education, and the erosion of autonomy. *The International Journal of Applied Philosophy, 20*(1), 67–79.

Schneider-Kamp, Anna, & Askegaard, S. (2020). Putting patients into the centre: Patient empowerment in everyday health practices. *Health, 24* (6), 625–645.

Sevastianova, V. N. (2023). Trademarks in the age of automated commerce: Consumer choice and autonomy. *IIC-International Review of Intellectual Property and Competition Law*, *54*(10), 1561-1589.

Siipi, H. and Uusitalo, S. (2011). Consumer autonomy and availability of genetically modified food. *Journal of Agricultural and Environmental Ethics, 24*(2), 147–163.

Sneddon, A. (2001). Advertising and deep autonomy. *Journal of Business Ethics, 33*(1), 15–28.

Strack, F., Werth, L., & Deutsch, R. (2006). Reflective and impulsive determinants of consumer behavior. *Journal of Consumer Psychology, 16*(3), 205-216.

Sunstein, C. R. (2016). Fifty shades of manipulation. *Journal of Marketing Behavior, 1*(3–4), 214–244.

Thaler, R. H. & Sunstein, C. R. (2009). *Nudge: Improving decisions about health, wealth, and happiness*. Penguin.

Verplanken, B. & Sato, A. (2011). The psychology of impulse buying: An integrative self-regulation approach. *Journal of Consumer Policy, 34*(2), 197–210.

Villarán, A. (2017). Irrational advertising and moral autonomy. *Journal of Business Ethics 144* (3), 479–490.

Wertenbroch, K., Schrift, R. Y., Alba, J. W., Barasch, A., Bhattacharjee, A., Giesler, M., Knobe, J., Lehmann, D.R., Matz, S., Nave, G., Parker, J.R., Puntoni, S., Zheng, Y., & Zwebner, Y. (2020). Autonomy in consumer choice. *Marketing Letters*, *31*, 429-439.

Wertheimer, A. (2014). Against autonomy? *Journal of Medical Ethics, 40*(5), 351-352.

Wood, M. (1998). Socio-economic status, delay of gratification, and impulse buying. *Journal of Economic Psychology, 19*(3), 295–320.

Yi, S. & Baumgartner, H. (2011). Coping with guilt and shame in the impulse buying context. *Journal of Economic Psychology, 32*(3), 458–67.

Zhu, T., Zhang, L., Deng, H., Liu, C. & Liu, X. (2024). Consumer autonomy: A strategy to alleviate the self-serving bias in tourism value co-creation. *Journal of Hospitality and Tourism Management*, *60*, 72-81.

Chapter 10

Artificial Intelligence and The Unfairness of Pricing Strategies

Aylin Atasoy[1]

Abstract

The rapid advancement of artificial intelligence (AI) and digital technologies has transformed pricing strategies, enabling firms to implement algorithmic and dynamic pricing models. While these strategies enhance efficiency and profitability by leveraging big data and predictive analytics, they also raise significant ethical concerns. This study explores the fairness of AI-driven pricing, particularly in the context of personalized pricing strategies that adjust prices based on consumer data. Drawing from theoretical frameworks such as price fairness, distributive justice, and trust theory, the study examines consumer reactions to algorithmic pricing and the implications for long-term business-consumer relationships.

Empirical evidence suggests that personalized pricing can lead to perceptions of unfairness, especially when consumers are unaware of price differentiation or feel manipulated. While businesses argue that data-driven pricing enhances market efficiency, critics highlight risks such as privacy violations, algorithmic biases, and economic discrimination. Furthermore, AI-driven pricing strategies may exacerbate social inequalities, particularly when used in essential services such as transportation and healthcare.

This study underscores the need for balancing profit-driven pricing models with ethical considerations to maintain customer trust and social responsibility. As AI continues to shape market dynamics, a responsible approach to algorithmic pricing will be essential in fostering ethical business practices and ensuring long-term sustainability.

1 İstanbul Gelişim Üniversitesi, İİSBF Havacılık Yönetimi

https://doi.org/10.58830/ozgur.pub710.c3027

1. Introduction

The development of digital technologies has changed many dynamics in the business world, and marketing has been part of this change. First and foremost, digital information technologies have made it much easier to access consumer data and use it to make decisions much more quickly. It is understood that marketing will have to be based on data, using predictive and contextual models, using the capabilities of artificial (or augmented) intelligence, augmented reality, becoming augmented marketing(Reis, 2022, p.8).

In Global audit, consulting and research firm Deloitte's Digital Marketing 2025 report (2024, p.4) we see that for CMOs, the top three priorities in the face of existing potential economic challenges are, firstly, accelerating the transition to new technologies such as AI, secondly, growth, expansion into new markets, segments and geographies, and thirdly, implementing systems and/or algorithms to improve customer personalisation.

It is noteworthy that two of the top three priorities of senior marketing executives are digitalisation and improving customer personalisation. The use of digital technologies has facilitated the tracking of customers' consumption habits and purchasing behaviour, enabling the provision of special offers, particularly with the use of personalised prices to enhance their appeal. Information technologies enable businesses to collect vast quantities of customer data at negligible cost and on a full-time basis (DalleMule & Davenport, 2017, p.112). This data can then be analysed to create sophisticated pricing strategies and personalised price recommendations based on these strategies (Priester et al., 2020, p.99).

In contemporary business organisations, there is a growing prevalence of units dedicated to the management of data, in addition to the establishment of marketing departments. These departments facilitate the creation of bespoke and personalised offers for customers, with these offers being informed by the data collected about the customers in question. The utilisation of sophisticated software and applications facilitates the aggregation of internet search behaviour, GPS location, and the diverse digital footprints emanating from individuals' digital devices. Through the analysis of this data, organisations are able to personalise advertisements, products, and services, particularly in regard to pricing, aligning with the specific needs and preferences of customers (Dubus, 2024, p.1).

The present study will focus on the extent to which the use of artificial intelligence in dynamic pricing systems is fair and ethical in terms of personalised price offers to consumers. Recent research on this subject will be referenced. The first section will emphasise the concept of price fairness. The second section will discuss research results on dynamic pricing and the use of artificial intelligence. The third section will discuss pricing strategies created by using data collected through artificial intelligence from an ethical perspective.

2. Price Fairness Concept

In early 2000, consumers noticed that Amazon was listing a DVD at different prices for different users. They then complained extensively on the company's chat boards and pressured the company to stop using the strategy of offering customers different prices for the same product (Lyn Cox, 2001, p. 264). A more recent case of differential pricing occurred on a travel platform. On the same day, a customer requested a quote from the same hotel for accommodation with three different brands of phones and the company offered different offers for each phone. Interestingly, the Iphone brand phone was offered higher than the others. Similarly, a passenger wanted to book a seat in the same class on the same flight for himself and his mother in 2022. However, the system offered his mother a cheaper price than him. In the face of different pricing for the same product, the customer expressed dissatisfaction with the unequal treatment as well as the unequal pricing (Ying et al. 2024, p.1).

Price fairness perceptions are influenced by multiple theoretical frameworks.The **Dual Entitlement Principle** (Kahneman, Knetsch, & Thaler, 1986) suggests that consumers expect fairness in transactions, accepting price increases due to rising costs but rejecting those solely for profit maximization. **Equity Theory** (Adams, 1965) and **Distributive Justice** (Homans, 1961) emphasize fairness based on input-output comparisons, where paying more than others for the same product is perceived as unjust. **Procedural Justice** (Thibaut & Walker, 1975) highlights the role of transparent and logical pricing mechanisms in shaping fairness perceptions. Similarly, **Social Comparison Theory** (Major & Testa, 1989) suggests that consumers judge fairness by comparing their price with others'. **Attribution Theory** (Weiner, 1985) explains that perceived fairness depends on whether price changes are attributed to controllable or external factors. **Trust Theory** (Mayer, Davis, & Schoorman, 1995) posits that consumer trust moderates reactions to pricing, with loyal customers being more tolerant unless they feel betrayed. Finally, **Perceived Fairness & Emotions** (Campbell, 2004) highlights the emotional dimension of fairness, where perceived price unfairness can trigger negative reactions such as anger, complaints, or negative word-of-mouth (Xia et al. 2004, p.1)

In the contemporary context, customers encountering varied prices for similar products on travel platforms may discern that these fluctuations are precipitated by numerous factors. Nevertheless, the rationales underlying price changes are frequently opaque, particularly in the context of transparent pricing practices being uncommon in the travel industry (Chung & Petrick, 2013). This engenders the perception of price fairness becoming a pivotal issue for both consumer experience and business interests. Personalised pricing has been shown to erode consumer loyalty and diminish purchase intentions by eliciting feelings of unfairness (Richards et al., 2016). In the long term, such practices can adversely impact corporate interests. Furthermore, while some tourists may exhibit self-protective or vindictive behaviour in response to price injustice, others may choose to remain indifferent. For instance, the study on the perception of price fairness on online travel platforms, published in 2024, concluded that the pricing practices of travel platforms are not yet aligned with customers' expectations of market fairness, suggesting that platforms should act in accordance with industry norms and ethical standards to maintain consumer trust (Ying et al., 2024, p. 9).

Trough the theoretical foundation for understanding how consumers perceive price fairness it is obvious that fairness judgments are not solely based on price levels but also on the rationale behind price changes, transparency, social comparisons, and emotional responses. Consumers accept price increases when they are justified by external factors, such as rising costs, but view them as unfair when they appear to be driven purely by profit motives. Social and comparative dimensions also play a crucial role, as individuals evaluate fairness relative to what others pay. Additionally, procedural aspects, such as transparency in pricing, influence fairness perceptions. Trust in the seller moderates consumer reactions, with loyal customers showing more tolerance unless they feel deceived. (Khandeparkaret. al 2020). Ultimately, fairness perceptions are not only cognitive but also emotional, meaning that unfair pricing can lead to strong negative responses, such as complaints and negative word-of-mouth (van Boom, et.al 2020).. This interpretation highlights the complexity of price fairness judgments and their implications for consumer behavior.

In the contemporary context, digital information technologies that process data collected through machine learning-based algorithms are supported by artificial intelligence to guide pricing strategies. These digital technologies are both faster and more accurate than the work to be done with human intelligence and are competent enough to manage the perception of customers. However, on the other hand, they also affect the perception of price fairness.In this context, it is important to know which factors affect the perception of price fairness. The following components, as outlined by the framework developed by Xia et al. (2004, pp. 1-2), have been identified as influential factors in determining consumers' perceptions of price fairness:

i) transaction similarity and the selection of the comparison party;

ii) the allocation of costs and profits with the concomitant attribution of responsibility;

iii) the status of the buyer-seller relationship (trust); and

iv) knowledge, beliefs, and social norms.

The interplay of these factors collectively influences consumers' cognitive and emotional perceptions of price fairness. In addition, depending on the perceived value and emotions, they also affect the decision-making process of consumers. Some consumers may not take any action, while others may consider taking revenge. Some customers even report deficiencies related to price unfairness and socially unfair behaviour (Martin et al. 2009).

3. Dynamic Pricing and Artificial Intelligence

The concept of dynamic pricing, which gained prominence in the 1980s following its successful implementation by American airlines, also resulted in the adoption of algorithmic pricing. While the mathematical concepts and models underpinning dynamic pricing can be traced back to the mid-twentieth century, it was the seminal scientific papers of Peter Belobaba (1987, 1989) in the late 1980s and early 1990s that generated increased interest in practical studies (Seele et al. 2019, 700).

Personalised pricing is predicated on the utilisation of algorithmic pricing, a practice that airline companies have employed in revenue management software for a considerable duration. In its nascent form, the software's pricing mechanisms were governed by instructions provided by a programmer.Contemporary algorithms, however, are driven by artificial intelligence and exhibit a marked increase in autonomy when compared with their antecedents. These advanced algorithms have evolved to formulate pricing strategies through active experimentation and in accordance with the evolving or changing environment. They demonstrate a high degree of autonomy and require minimal or no instruction from an external programmer. However, the employment of algorithms in pricing strategies gives rise to legal and ethical concerns. These algorithms may be designed to orchestrate price increases or diminished competition, obviating the need for direct communication or agreement (Calvano et al., 2020, pp.3-4). This may present challenges in terms of competition law and consumer rights, potentially necessitating the establishment of regulatory frameworks to promote the development of more transparent and auditable algorithms.

There are different types of algorithmic pricing. The best known of these is dynamic pricing. Dynamic pricing, sometimes referred to as surge, yield, or real-time pricing, refers to the practice of dynamically adjusting prices to realise revenue gains when responding to a specific market situation with uncertain demand. Personalised pricing can also be seen as first-order price discrimination, customised or targeted pricing and represents a pricing strategy in which 'firms charge different prices to different consumers according to their willingness to pay' (Seele et al. 2019, pp. 699).

Demand forecasting, flexibility and the willingness to pay are pivotal to a profitable pricing strategy. For instance, a study conducted in the context of grocery retailers (Srinivasan et al., 2008) found that demand assessments, rather than changing prices from week to week based on wholesale costs and competition, lead to higher profits. Dynamic pricing also micro-segments the market by person, product, period and location in order to adjust the price. Prices are adjusted as these four basic dimensions change. (Kopalle et al. 2023, p.581)

Industries such as supermarkets, airlines and credit card companies collect traces left by individual consumer transactions in large databases to examine purchasing patterns and offer personalised price offers through targeted marketing strategies. On the one hand, there are those who argue that consumers served at higher prices have the potential to affect competition and that this situation will lead companies to abandon dynamic pricing. However, an analysis of actual market behaviour reveals that price adjustments based on customer segments do not necessarily result in reduced profits for companies, even when consumers are aware of these strategies (Laussel & Resende, 2022).

Algorithmic pricing has emerged as a crucial aspect of dynamic pricing in response to changes in customer segments. Wang, Li, and Kopalle (2022) define algorithmic pricing as the use of artificial intelligence algorithms by businesses to identify, analyze, and offer personalized prices to consumers. Today, companies equipped with advanced big data analytics can effortlessly track consumers' digital footprints to determine their preferences. In the retail sector, Target analyzes customers' past shopping behaviors to provide personalized discount coupons. Similarly, in the travel and hospitality sector, Orbitz engages in price discrimination by tracking online browsing activities The use of consumer data is not limited to online retailers but extends to physical stores as well. For instance, Amazon's cashierless "Amazon Go" stores utilize cameras and sensors to identify customers, monitor their in-store movements and product interactions, and offer personalized discounts (Vandervoort, (2024). In China, particularly among luxury brands, stores employ facial recognition technology at entrances to identify individuals and implement personalized pricing strategies (Wong, 2018).

4. Ethical Aspect of Pricing Strategies

The use of algorithmic pricing and data-driven personalisation in competitive markets has ethical implications for customer privacy. While competition requires independent decision-making, Gal (2019) highlights how algorithms now enable autonomous price coordination, potentially leading to implicit collusion among competitors. This raises legal concerns, particularly when algorithms are designed to react to competitors' pricing decisions in a way that maintains coordinated market outcomes.

Simultaneously, businesses leverage vast data resources to enhance personalized marketing strategies, shifting from broad customer segmentation to individualized targeting. However, Turow (2017, pp. 247–248) in his book "*The aisles have eyes: How retailers track your shopping, strip your privacy, and define your power*" warns of ethical dilemmas in this practice, as algorithms may facilitate social discrimination by tailoring messages and prices based on consumer profiles 'often without the individuals' awareness or consent. These developments underscore the tension between technological advancements, market fairness, and ethical considerations in modern digital economies.

It is also addresses the legal accountability of algorithm designers and users in cases of potential anti-competitive behavior. The European Commissioner for Competition emphasizes that businesses remain responsible for the consequences of the algorithms they implement. Legal liability arises when a company is aware of the algorithm's pricing effects, as demonstrated in the *Eturas* case, where 30 Lithuanian travel agencies used a shared booking system that restricted discounts. The European Court of Justice ruled that awareness of the algorithmic restriction was necessary to establish a cartel agreement, though indirect awareness—such as ignoring the algorithm's potential effects—could also be relevant. However, the legal framework remains unclear regarding situations where algorithms autonomously determine pricing strategies and facilitate collusion without explicit human intervention. This ambiguity raises ongoing legal and ethical challenges in regulating algorithmic decision-making in competitive markets (Gal, 2019, p.20).

Personalised pricing is a tool utilised across various sectors, with its efficacy in enhancing business profitability being particularly pronounced in contexts characterised by minimal marginal costs of production (Coker & Izaret, 2021, p.387). To illustrate this point, consider the observation made by Shiller (2016, p.7), who asserts that Netflix could potentially augment its profits by up to 15% through the strategic tailoring of its pricing structure to customers' web browsing histories.

Steinberg (2020) critiques big-data-driven personalized pricing, arguing that its exclusive use for profit maximization disrupts the fair distribution of economic benefits. He asserts that such pricing strategies deepen power asymmetries between consumers and firms, undermining relational equality in market transactions. By making it prohibitively difficult for consumers to compare prices or negotiate, personalized pricing diminishes their agency as market participants, effectively limiting their ability to make informed purchasing decisions. This perspective highlights the ethical concerns surrounding the practice, suggesting that personalized pricing may be morally indefensible if it violates principles of fairness, equal treatment, and market accessibility.

It is the right of consumers to demand transparency regarding the benefits they accrue from specific market practices, particularly in terms of price. Previous research suggests that consumers' acceptance of a price depends on their perception of its fairness, which is judged by whether a transaction is reasonable, acceptable, or just. Unfair pricing practices trigger negative consumer reactions, including distrust, reduced purchase intentions, and increased likelihood of switching to competitors. Moreover, perceived price unfairness leads to negative word-of-mouth, both privately and publicly, further harming a company's reputation and customer loyalty (Hufnagel et al. 2022, p.347). For consumers, lack of transparency in pricing leads to the perception of arbitrary pricing, which may lead to scepticism and questioning of the firm's credibility.

The increasing role of digitalisation and algorithmic decision-making in dynamic pricing highlights the technological advances that are transforming pricing strategies. The rise of online retail, digital travel booking, and mobile commerce, accelerated by the COVID-19 pandemic, has enabled real-time, personalized pricing. Innovations such as electronic shelf labels in physical stores allow retailers to adjust prices dynamically, bridging the gap between online and offline pricing. Additionally, the shift from human-driven to algorithmic-driven pricing decisions has led to autonomous pricing agents setting prices without direct managerial intervention. This automation reduces the cost of price adjustments, making dynamic pricing more accessible and widely adopted (Kopalle et al., 2023, p.589)

On the other hand it must be noted that dynamic pricing enabling price collusion, which can lead to monopolistic or oligopolistic practices. Legal cases, such as the 2015 "Poster Cartel" case on Amazon, have demonstrated how pricing algorithms can be used to maintain price parity among vendors, effectively preventing price competition. While some cases involve explicit collusion where vendors coordinate pricing strategies more concerning is tacit collusion, where autonomous pricing algorithms unintentionally synchronize prices without direct human intervention. This occurs due to advanced machine learning techniques, such as reinforcement learning, which allow algorithms to adjust prices in response to competitors' pricing patterns. Two key challenges arise from this: first, existing legal frameworks focus on human collusion, making algorithm-driven collusion difficult to regulate; second, the complexity and speed of algorithmic pricing make it difficult to detect and analyze collusion, requiring extensive computational resources. These factors present significant ethical and regulatory challenges in the use of dynamic pricing. (Nunan & Di Domenico, 2022, pp.454-455).

There are studies that argue against the ethics of price customization. Marcoux (2006) and Elegido (2014) have conducted studies that argue that it is more ethical to offer the same product to different consumers at different prices, namely through price customization, with a unitary price set under open market conditions. A comprehensive review by Coker and Izaret (2021) opposes these studies and argues that price customization is more ethical than unitary pricing. Through a structured example involving these two consumer types, they evaluate price personalization using four Social Welfare Functions (SWFs)—utilitarian, egalitarian, prioritarian, and leximin. Their findings indicate that price personalization enhances overall social welfare across all four SWF perspectives. Ultimately, they conclude that personalized pricing not only increases total welfare but also benefits consumers, challenging traditional ethical concerns associated with differential pricing strategies (Mazrekaj et al.2024)

Besides these studies Mazrekai et al (2024) evaluates the ethical implications of unitary versus personalized pricing through the lens of four consequentialist Social Welfare Functions (SWFs). Their findings challenges the conclusions of Coker and Izaret (2021), who argued that personalized pricing is ethically superior due to its ability to increase both utility and equity. The authors caution that this conclusion is contingent on the assumption that wealthier individuals derive higher utility from a product. When this assumption is relaxed, the ethical advantage of personalized pricing diminishes, particularly if consumers perceive it as unfair or feel their privacy is violated by AI-driven willingness-to-pay (WTP) estimations. The study suggests that unitary pricing may often be preferable if personalized pricing results in a welfare loss, especially when product utility is significant for lower-income consumers. More broadly, the findings highlight the need for a nuanced approach to ethical evaluations, as different economic and behavioral conditions can lead to unexpected reversals in outcomes.

Algorithmic price personalization has an impact on consumer perceptions of fairness. Zuiderveen Borgesius & Poort (2017, p.354) argue that consumers feel wronged when charged higher prices than others, perceiving such practices as unfair or manipulative, which can lead to reduced demand. Hermann (2022, p.52) further emphasizes the ethical dilemmas associated with algorithm-driven pricing, particularly its potential to reinforce social inequalities. When algorithms segment populations based on demographic factors, they may unintentionally favor or disadvantage certain customer groups. Biases in algorithmic predictions can stem from skewed data, including disproportionate representation of certain groups, misleading proxy variables, or insufficient data, leading to unfair and discriminatory outcomes. Mazrekaj et al. (2024) reinforce this concern by stressing that these biases can result in unequal treatment of individuals, raising significant ethical and fairness-related challenges in algorithmic pricing strategies.

Empirical research consistently demonstrates that consumers perceive personalised pricing as unfair or manipulative (Anderson & Simester, 2010; Krämer et al., 2018; Turow et al., 2005). A survey that was held by Turow and his friends (2005) in USA about online an doffline shopping and price discrimination. The study reached to 1,500 U.S. adults and revealed that 76% of respondents expressed concern regarding others paying less for the same product. On the other hand 64% of American adults who have used the internet for shopping do not know it is legal for "an online store to charge different people different prices at the same time of day." 71% don't know it is legal for an offline store to do that. And also 75% do not know that besides a website has a privacy policy, it may share the information of the visiters with other websites and companies. (Turow et al., 2005, p.3). Price discrimination is frequently perceived negatively, even when it benefits the consumer, as evidenced by the fact that 72% of respondents disagreed with the notion that stores should offer them lower prices to retain their loyalty. The perception of unfair pricing has been demonstrated to have significant consequences, with Anderson and Simester (2010, p.729) finding in a randomised field experiment involving over 50,000 customers that consumers who discovered price disparities were less likely to make future purchases from the retailer. These findings highlight the potential negative impact of personalised pricing on consumer trust and long-term business relationships.

According to the study of Krämer et al., (2018) about airline pricing driven by low-cost carriers, consumer knowledge about personal pricing is crucial in determining whether they perceive a deal as fair. Resistance to personal pricing is expected due to concerns over privacy, data sharing, and perceived price manipulation. In the short term, airlines that refrain from using personalized dynamic pricing may gain a competitive edge if customers feel exploited. However, if all major carriers adopt personalized dynamic pricing, customers may have no alternative but to accept it—much like how revenue management and advance purchase restrictions became industry norms despite initial resistance.

Nevertheless, gaining customer acceptance for personalized dynamic pricing will be more challenging than implementing traditional revenue management practices. From the airlines aspect to be successful, airlines must effectively communicate and justify personalized pricing as fair, especially as privacy and discrimination concerns become widespread. At that point two key risks require further analysis: first, whether personalized pricing provides meaningful value to customers despite its economic advantages, and second, whether the short-term revenue gains from real-time willingness-to-pay estimation outweigh the long-term risks of damaging customer relationships. Ultimately, consumer perceptions of fairness (Alderighi et al., 2022) will be crucial in determining the viability and success of personalized dinamic prising in the airline industry.

An important disccusion point is the ethical concerns surrounding digital surveillance and privacy in the context of personalized pricing. Unlike the "access-view" of privacy, where individuals simply relinquish their data, people selectively share information with third parties while maintaining expectations about its scope, access, and usage. Ethical concerns arise when consumers feel coerced into sharing their data, such as when insurance companies charge higher premiums to those unwilling to disclose personal information. Loi et al. (2022, p.8) argue that this a practice that constitutes psychological coercion. This form of digital surveillance not only undermines privacy preferences but also limits individual autonomy, authenticity, and spontaneity in decision-making. Since personalized pricing relies on algorithms that estimate a consumer's willingness-to-pay using collected data, it may create a sense of being monitored, leading to a perceived loss of utility (Priester et al., 2020; Turow et al., 2015; Zuiderveen Borgesius & Poort, 2017). Some individuals may reject data-sharing entirely, not because of specific consequences, but because they intrinsically value privacy (Loi et al., 2022). These concerns highlight the ethical and psychological implications of data-driven pricing strategies.

5. Conclusion

As artificial intelligence and data-driven strategies continue to reshape pricing mechanisms, the ethical and practical implications of algorithmic pricing become increasingly significant. While dynamic pricing offers firms a powerful tool to optimize revenue and balance supply and demand, its implementation must be approached with caution. The intersection of AI and pricing strategies presents both opportunities and challenges—ranging from increased efficiency to concerns over fairness, transparency, and consumer trust.

Striking a balance between profitability and ethical responsibility is crucial for businesses aiming to maintain long-term customer relationships. As discussed, algorithmic pricing can inadvertently lead to consumer dissatisfaction, particularly when price adjustments appear exploitative or opaque. In industries where pricing directly affects essential services, such as transportation and healthcare, the need for responsible governance becomes even more pronounced. Regulatory oversight, corporate self-regulation, and interdisciplinary collaboration between scholars and practitioners will play a pivotal role in shaping the future of fair and effective pricing strategies.

Moving forward, businesses must not only refine their AI-driven pricing models to enhance accuracy and adaptability but also integrate ethical considerations into their decision-making processes. Transparent communication, consumer education, and proactive policy-making will be essential in ensuring that AI-powered pricing benefits both businesses and society at large. By fostering a responsible approach to pricing strategy, firms can harness the advantages of AI while mitigating risks, ultimately creating a more sustainable and consumer-centric marketplace.

References

Adams, J.S. (1965), "Inequity in Social Exchange," in *Advances in Experimental Social Psychology*, Vol. 2, L. Berkowitz, ed. New York: Academic Press, 267–299.

Alderighia, M., Navab, C.R., Calabresed,M., Christilled, J.M.&Salveminid; C.B.(2022).Consumer perception of price fairness and dynamic pricing:Evidence from Booking.com. *Journal of Business Research*, 145, pp.769–783

Allender,W.J. Liaukonyte, J., Nasser, S.& Richards, T.J. (2021). Price Fairness and Strategic Obfuscation, *Marketing Science*, 2021, 40 (1), pp. 122–146.

Anderson, E. T., & Simester, D. I. (2010). Price Stickiness and customer antagonism. *The Quarterly Journal of Economics, 125*, 729–765.

Belobaba, P. P. (1987). *Air travel demand and airline seat inventory management*. Working Paper/Dissertation. Ph.D. dissertation. Cambridge, MA : Flight Transportation Laboratory, Massachusetts Institute of Technology. Retrieved from https ://dspac e.mit.edu/handl e/1721.1/68077.

Belobaba, P. P. (1989). OR practice: Application of a probabilistic decision model to airline seat inventory control. *Operations Research, 37*(2), 183–197. https ://doi.org/10.1287/ opre.37.2.183.

Bettray, J., Suessmair, A. and Dorn, T. (2017) Perceived Price Fairness in Pay-What-You-Want: A Multi-Country Study. *American Journal of Industrial and Business Management*, 7, 711-734.

Calvano, E., Calzolari, G., Denicolo, V., Pastorello, S., (2020). Artificial intelligence, algo-rithmic pricing, and collusion. American Economic Review, 110 (10), 3267–3297.

Campbell, M. (2004). Who Says? How the Source of Price Information and the Direction of Price Change Influence Perceptions of Price Fairness, working paper, Department of Marketing, University of Colorado, Boulder.

Chung, J. Y., & Petrick, J. F. (2013). Price fairness of airline ancillary fees: An attributional approach. *Journal of Travel Research, 52*(2), 168–181. https://doi.org/ 10.1177/0047287512457261

Coker, J., & Izaret, J.-M. (2021). Progressive pricing: The ethical case for price personalization. *Journal of Business Ethics, 173*, 387–398.

DalleMule, L., & Davenport, T.H., 2017. What's your data strategy. *Harvard Business Review*. 95 (3), 112–121.

Deloitte Digital, (2024). Embracing change and gearing up for the future https://www.deloittedigital.com/content/dam/digital/nl/pdfs/marketing-trends-2025-final.pdf

Dubus, A. (2024). Behavior-based algorithmic pricing, *Information Economics and Policy,* 66,101081

Elegido, J. M. (2011). The ethics of price discrimination. *Business Ethics Quarterly, 21*(4), 633–660.

Gal, M.S. 2019. Illegal pricing algorithms. *Communications of the ACM* 62 (1): 18–20. https ://doi.org/10.1145/32925 15.

Gerlick, J.A. & Liozu, S.M. (2020). Ethical and legal considerations of artificial intelligence and algorithmic decision-making in personalized pricing, *Journal of Revenue and Pricing Management*, 19:85–98.

Hermann, E. (2022). Leveraging artificial intelligence in marketing for social good - An ethical perspective. *Journal of Business Ethics, 179*, 43–61. https:// doi. org/ 10. 1007/s10551- 021- 04843-y

Homans, G.C. (1961), *Social Behavior: Its Elementary Forms*. New York: Harcourt, Brace & World.

Hufnagel, G. Manfred Schwaiger, M. & Weritz, L. (2022). Seeking the perfect price: Consumer responses to personalized price discrimination in e-commerce. *Journal of Business Research*, 143, pp.346–365.

Kahneman, D., Jack L. Knetsch, &Thaler, R. (1986), Fairness and the Assumptions of Economics, *Journal of Business*, 59 (4), 285–300.

Kopalle, P.K., Paulwels, K., Akella, L.Y. & Gangwar, M. (2023). Dynamic pricing: Definition, implications for managers, and future research directions. *Journal of Retailing*, 99, 580–593.

Khandeparkar, K., Maheshwari, B., & Motiani, M. (2020). Why should I pay more? Testing the impact of contextual cues on perception of price unfairness for the price-disadvantaged segment in dual pricing. *Tourism Management, 78*, Article 104075. https://doi.org/10.1016/j.tourman.2020.104075

Krämer, A., Friesen, M., & Shelton, T. (2018). Are airline passengers ready for personalized dynamic pricing? *Journal of Revenue and Pricing Management, 17*, 115–120.

Laussel, D. & Resende, J.(2022) When Is Product Personalization Profit-Enhancing? A Behavior-Based Discrimination Model. *Management Science,* 68(12), pp.8872-8888.

Loi, M., Hauser, C., & Christen, M. (2022). Highway to (Digital) Surveillance: When are clients coerced to share their data with insurers? *Journal of Business Ethics, 175*, 7–19. https:// doi. org/ 10. 1007/ s10551- 020- 04668-1

Lyn Cox, J. (2001). Can differential prices be fair? *The Journal of Product and Brand Management, 10*(5), 264–275. https://doi.org/10.1108/10610420110401829

Major, B. & Testa, M. (1989), Social Comparison Processes and Judgments of Entitlement and Satisfaction, *Journal of Experimental Social Psychology*, 25 (2), 101–120.

Marcoux, A. (2006). Much ado about price discrimination. *Journal of Markets and Morality, 9*(1), 57–69.

Martin, W. C., Ponder, N., & Lueg, J. E. (2009). Price fairness perceptions and customer loyalty in a retail context. *Journal of Business Research, 62*(6), 588–593. https://doi. org/10.1016/j.jbusres.2008.05.017

Mayer, R C., Davis, J:H.& Schoorman, F.D. (1995). An Integrative Model of Organizational Trust," *Academy of Management Review*, 20 (3), 709–734.

Mazrekaj,D.,Verhagen, M.D., Kumar, A. & Daniel Muzio, D. (2024). Does Price Personalization Ethically Outperform Unitary Pricing? A Thought Experiment and a Simulation Study. *Journal of Business Ethics*, https://doi. org/10.1007/s10551-024-05828-3

Nunan,D. & Di Domenico, M.L. (2022). Value creation in an algorithmic world: Towards an ethics of dynamic pricing. *Journal of Business Research*, 150, pp.451–460

Priester, A., Robbert, T. & Roth, S. (2020). A special price just for you: effects of personalized dynamic pricing consumer fairness perceptions. *Journal of Revenue and Pricing Management*, 19, pp.99–112.

Reis, J. L. (2022). Artificial Intelligence impact in marketing. In Silva, P. & Teixeira, F. (Orgs.). Digital Marketing Trends (pp. 7-10). Porto. CEOS Publicações.

Richards, T. J., Liaukonyte, J., & Streletskaya, N. A. (2016). Personalized pricing and price fairness. *International Journal of Industrial Organization, 44*, 138–153. https:// doi.org/10.1016/j.ijindorg.2015.11.004

Seele, P., Dierksmeier, C., Hofstetter, R., & Schultz, M. D. (2019). Mapping the Ethicality of Algorithmic Pricing: A review of Dynamic and Personalized Pricing. *Journal of Business Ethics,* 170(4), 697–719.

Shiller, BR (2016). Personalized price discrimination using big data. *Brandeis university working paper series, 108*, 1–39.

Srinivasan, S., Pauwels, K.. & Nijs, V. (2008), Demand-based pricing versus past-price dependence: A cost–benefit analysis. *Journal of Marketing*, 72 (2), 15–27.

Steinberg, E. (2020). Big data and personalized pricing. *Business Ethics Quarterly, 30*(1), 97–117.

Thibaut, J.W. and L. Walker (1975). *Procedural Justice: A Psychological Analysis*. Hillsdale, NJ: Lawrence Erlbaum Associates

Turow, J., Feldman, L., & Meltzer, K. (2005). Open to Exploitation: America's Shoppers Online and Offline. *A Report from the Annenberg Public Policy Center of the University of Pennsylvania*, Retrieved from http:// repos itory. upenn. edu/ asc_ papers/ 35.

Turow, J. 2017. *The aisles have eyes: How retailers track your shopping, strip your privacy, and define your power*. New Haven: Yale University Press.

Vandervoort, O. (2024). Amazon Go stores: How the 'Just walk out' cashier-less tech works

https://www.pocket-lint.com/what-is-amazon-go-where-is-it-and-how-does-it-work/ (Access date 17.03.2025)

van Boom, W. H., van der Rest, J. P. I., van den Bos, K., & Dechesne, M. (2020). Consumers beware: Online personalized pricing in action! How the framing of a mandated discriminatory pricing disclosure influences intention to purchase. *Social Justice Research, 33*(3), 331–351. https://doi.org/10.1007/s11211-020-00348-7

Wang, Xin, Li Xi and Kopalle Praveen K. (2022), "When does it pay to invest in pricing algorithms?," *Production and Operations Management*.

Weiner, B. (1985). An Attributional Theory of Achievement Motivation and Emotion, *Psychological Review*, 92 (4), 548–73.

Wong, T. (2018). China's retailers turn to real-world surveillance to track big spenders. Wired. https://www.wired.com/story/retail-surveillance-china/ (Access date: 17.03.2025)

Xia, L., Monroe, K. B., & Cox, J. L. (2004). The price is unfair! A conceptual framework of price fairness perceptions. *Journal of Marketing, 68*(4), 1–15. https://doi.org/ 10.1509/jmkg.68.4.1.42733

Ying,T., Zhou, B., Ye, S. , Shihan (David) M.&Tan, X. (2024). Oops, the price changed! Examining tourists' attribution patterns and blame towards pricing dynamics. *Tourism Management,* 103, 104890

Zuiderveen Borgesius, F., & Poort, J. (2017). Online price discrimination and EU data privacy law. *Jounral of Consumer Policy, 40*, 347–366.

Bölüm 11

Fake Reviews and Ratings Undermining Consumer Trust

Haydar Özaydın[1]

Abstract

With Internet technologies and e-commerce systems, consumers can access information about products, services and brands. One of the most effective tools they can access is the ability to access and write reviews about the products and services they have purchased. These reviews and ratings in various online channels such as social media, e-commerce websites or online evaluation platforms have become important in directing consumers' purchasing processes and feelings of trust and can significantly affect consumer decisions. However, with the development of artificial intelligence technologies, the creation of fake reviews has become easier and widespread. Therefore, the prevalence of reviews manipulated to influence consumers may cause scepticism and distrust towards online platforms. This situation negatively affects consumer trust and creates information asymmetry between e-commerce platforms, businesses and consumers. Fake reviews and ratings create doubts about the accuracy and reliability of the information provided about the product/service. Online reviews and ratings cease to be a real source of business feedback. In addition, the research also discusses the contribution of artificial intelligence tools to avoid and detect the adverse effects of fake reviews and ratings. This research aims to examine the effects of fake reviews and ratings on consumer trust and evaluate how fake reviews and ratings are produced, their characteristics, and the research on detecting fake reviews.

1 Assistant Professor, Bolu Abant İzzet Baysal Üniveritesi, haydar.ozaydin@ibu.edu.tr, 0000-0003-0274-7143

https://doi.org/10.58830/ozgur.pub710.c3028

Introduction

With digital processes, consumer comments and feedback have become an important reference tool in consumers' purchasing decisions today. Although there are genuine consumer reviews and feedback in digital media, consumers' purchasing decisions can be manipulated by making fake reviews or ratings with artificial intelligence. As technology continues to develop, the ability of artificial intelligence to manipulate digital media is also improving. It is becoming increasingly difficult to distinguish what is real and what is artificially produced or manipulated, and it can pose significant challenges for consumers to make informed decisions based on accurate information. With the help of artificial intelligence, it is possible to produce fake reviews and ratings that appear to come from real users and to lead others to mislead and trust false information. Unfortunately, with the rise of technology comes the possibility of manipulation, and AI tools enable sophisticated algorithms that can generate fake reviews and ratings, convincing consumers that a product or service is better than it is.

These situations weaken consumers' trust and thus negatively affect their online shopping experience. When a shopping experience based on fake reviews or ratings results in a negative shopping experience, it creates dissatisfied consumers. Such manipulations can lead to processes that can threaten not only individual consumers' experiences but also businesses' reputation. Therefore, fake reviews and ratings prevent consumers from accessing accurate information about products and services, increasing information asymmetry and disrupting market order (Malbon, 2013).

The reliability of these reviews, which affect consumers' online shopping decisions, is important for both businesses and consumers. As Mathews Hunt, (2015) states in his study, online reviews play an important role in consumers' evaluations of products and services. However, the increase in fake reviews and the involvement of artificial intelligence in this process question the reliability of these reviews and weaken consumers' trust in online platforms. In this context, detecting and preventing fake reviews is critical for consumer protection and market order (Mohawesh et al., 2021).

The effects of fake reviews on consumer trust have become an important research topic in digital marketing and e-commerce. Online consumer reviews are among the critical elements influencing consumers' purchasing decisions. However, the increase in fake reviews can damage consumer trust, which needs to be measured and analysed. In order to rebuild consumer trust, it is considered important to understand the effects of fake reviews and to take adequate measures. In this study, online consumer reviews and fake reviews are defined first. The concepts of fake reviews and consumer trust are expressed, and finally the studies in the literature on detecting fake reviews are discussed.

1. Online Consumer Reviews and Fake Reviews

Online consumer reviews can be expressed as user-generated opinions posted online by purchasers of products or services (Ma & Lee, 2014). The components of online consumer reviews include an overall star rating, clearly stated pros and cons, and free text comments. The consistency of these components provides an important data source for product assessments (Schindler & Decker, 2013). With the development of web technology and e-commerce, consumers increasingly rely on online reviews before making purchasing decisions (Song, Wang, Zhang, & Hikkerova, 2023). The first indicator in the consumer decision-making process is usually ratings, which indicate the user evaluation of a product and are expressed as asterisks. Ratings are applications that can deal with large amounts of information, are easy to process, and help identify selection criteria. Stars or scores, indicators of ratings, are effective because they are easily accessible information when selecting a product (Karaca & Gümüş, 2020). Therefore, online consumer reviews can be defined as any positive, negative or neutral comment, rating, ranking, assumed to be made by a former customer about a product, service, brand or person and shared with other consumers in an unstructured format such as a blog post or on an independent consumer review website (Filieri, 2016).

Today's consumers essentially see online consumer comments as a form of eWOM (electronic word-of-mouth) in the online and offline product purchase decision process. Electronic word-of-mouth can be defined as all positive or negative comments about the business, product or service on online platforms and all kinds of communication based on them. Compared to traditional word-of-mouth communication, online reviews and ratings have the potential to reach more people through the internet (Fong, 2010). Positive reviews can lead the consumer to purchase the product, while negative reviews can cause them to change their purchase decision. Thus, positive reviews result in significant product sales, financial gains or reputation for businesses and individuals. Online consumer reviews enable people to obtain detailed information with high credibility and reputation compared to information marketers provide (Akdeniz & Özbölük, 2019; Park & Nicolau, 2015). These advantages of consumer reviews can be an opportunity for many malicious practices (Algur, Patil, Hiremath, & Shivashankar, 2010).

Spam, fake, misleading and even fraudulent online reviews are rapidly growing and becoming widespread on the internet (Zhang, Du, Yoshida, & Wang, 2018). Fake reviews are manipulative attempts to manipulate consumers into thinking more favourably about a product or service than they do and to influence their purchasing decisions (Costa Filho, Nogueira Rafael, Salmonson Guimarães Barros, & Mesquita, 2023). From a business perspective, the purpose of online review manipulation is to strengthen the business's online reputation, attract consumers' attention and increase their tendency to purchase from the business (Sop, Atasoy, & Günaydin, 2024). Fake reviews are inconsistent with authentic reviews of products or services, so fake reviews are false and deceptive. They are deceptive reviews, often provided by reviewers with little or no experience of the products or services being reviewed, with the aim of misleading consumers in their purchasing decisions. The defining characteristic of fake reviews is whether they mislead consumers (Wu, Ngai, Wu, & Wu, 2020; Zhang, Zhou, Kehoe, & Kilic, 2016). The aim of fake reviewers, or deceivers in general, is to deceive others while trying to avoid detection. Motivated by financial gains or other benefits, fake reviewers can continuously improve themselves through previous experience to increase their chances of success (Zhang et al., 2016). Fake reviews reduce informativeness, information quality and the effective use of online product reviews. They can also damage the credibility of reviews, negatively impacting the benefits that reviews can provide. However, since consumers have little knowledge of who the reviewers are, it is normal for them to distrust both online platforms and reviews. The trustworthiness of the reviewer is important in consumers' perceptions of trust in online reviews and ratings (Evans, Stavrova, & Rosenbusch, 2021). In addition, fake reviews seriously negatively impact the development of online product reviews and create information asymmetry between merchants and customers. Online sellers may create positive fake reviews for their products or negative fake reviews for their competitors' products for financial gain (Sahut, Laroche, & Braune, 2024). The right marketplace for reviews also benefits companies, as they can get real customer feedback that can be analysed to improve products and services (Salminen, Kandpal, Kamel, Jung, & Jansen, 2022).

There are two types of fake comments. The first is fake reviews created by humans, and the second is computer-based fake reviews. Various methods of creating fake reviews can be expressed as follows (Ross, 2020; Salminen et al., 2022). Firms can use paid review services to share fake reviews for their products and services. These paid reviews are mostly seen on digital platforms like Google, Yelp or Amazon. Creating fake reviews through tools such as artificial intelligence and bots is also possible. Fake reviews can be made cheaper than paid reviews, especially with tools such as text natural language processing and machine learning. Finally, fake accounts can create negative comments on competitors' products and services and positive comments on their products and services. Other more complex forms of online review manipulation also exist, including ranking information provided to consumers by search engines. A wide range of manipulations of the loading time of web pages, their design and the way they present information are also among the conscious activities to which consumers are unwittingly exposed (Malbon, 2013).

2. Consumer Trust and Fake Reviews

Consumer trust underpins the long-term commercial relationship between seller and buyer. At its core, trust is about believing, trusting or having faith in an organisation, its staff and its services. It helps reduce perceived risk and is a valuable component of a business strategy as it positively influences buyers' purchasing decision by generating word-of-mouth communication (Bauman & Bachmann, 2017; Flanagan, Johnston, & Talbot, 2005). Trust is an important factor in the influence of online reviews and ratings (Fong, 2010). Online reviews and ratings have become an important and trusted source of information for consumers' decision-making processes (Evans et al., 2021).

Zhang, Chen, & Sun, (2010) found that sellers' reputation, information openness, and online consumer reviews positively affect consumer trust. This study emphasises that high-quality online reviews increase the seller's reputation and thus reinforce consumer trust. Utz, Kerkhof, & Van Den Bos, (2012) examined the effect of online store reviews on consumer trust. The study results show that consumer reviews are an important element in evaluating the trustworthiness of online stores. The authors state that consumer reviews are a more effective determinant of trust than store reputation. Lee, Park, & Han, (2011) found that the effect of online consumer reviews increases with higher trust in online shopping sites. In addition, the authors stated that online consumer reviews made by independent users affect consumers 'purchase intention more than consumer reviews directly integrated into sellers' advertisements. The quality and number of online reviews are important factors affecting consumer trust. A study by Zeng, Cao, Lin, & Xiao (2020) examined the relationship between the quality of online reviews and consumer behaviour. The research shows that the quality of online reviews directly impacts consumer intentions.

However, fake reviews and ratings have a negative impact on consumers' purchase decision processes and their sense of trust (Costa Filho et al., 2023). Wu & Qiu, (2016) state that low-quality sellers tend to write more fake reviews than high-quality sellers. This situation makes it difficult for consumers to evaluate the quality of the genuine product, thus weakening the sense of trust. However, Song et al., (2023) also stated that fake reviews for products with high brand awareness do not affect consumers' purchase intention. However, as the fake review rates of products with low brand awareness increase, consumers' purchase intention decreases.

He, Hollenbeck, & Proserpio, (2022) found in their research on the Amazon that fake reviews are purchased for products with low reviews, low ratings or new products that have just been released to the market. They stated that Amazon detects and deletes the reviews with the measures they take against fake reviews and ratings, but short-term unfair advantages are obtained due to the long duration of this process. The authors stated that fake reviews and ratings should not be perceived as an advertising activity but as a manipulation tool that damages consumers' trust.

Sop et al. (2024) reported that hotel managers manipulate negative reviews about their businesses by intervening with various methods. The authors stated that managers resort to various unethical service compensation methods, including having staff make comments as if they were customers, to prevent consumers from making negative reviews about the hotel and its services.

Fake reviews threaten the credibility of marketing and e-commerce. Fake reviews negatively affect consumer trust in online reviews, which can negatively affect the market order. Fake reviews can positively or negatively affect the ranking of products. The impact of fake reviews is not only limited to loss of reputation, but also has the potential to bring financial losses (Salminen et al., 2022). Measuring and analysing the effects of fake reviews on consumer trust requires a multidimensional approach. The research studies above provide different perspectives necessary to understand the adverse effects of fake reviews on consumer trust. The following section presents studies on detecting fake reviews and evaluations.

3. Fake Reviews Detection

Fake reviews are also known as deceptive opinions, spam reviews, while their authors are called spammers. They can cause financial loss for product manufacturers and service providers, as negative fake reviews can damage their brand reputation (Cardoso, Silva, & Almeida, 2018).

Some important features of fake reviews are the following (Alsubari et al., 2021; Hussain, Turab Mirza, Hussain, Iqbal, & Memon, 2020):

- **Insufficient information about the reviewer:** People who interact little in the relevant channel or comment without profile information are defined as fake reviewers.
- **Similar review content:** Fake reviewers often share similar reviews on the relevant channels.
- **Short Reviews:** Since fake reviewers are interested in fast returns, they share short reviews with spelling and grammar mistakes.
- **Sharing reviews at similar times:** To identify fake reviews, look at the time when they were shared. Fake reviews can sometimes be posted collectively at the same time.
- **Exaggerated reviews:** Fake reviewers often use overly positive and negative statements.

Hassan & Islam, (2021) researched using a sentiment analysis-based model to detect fake reviews online. According to the results obtained, they observed that online fake reviews are either positive or negative at extremes. In order to attract the attention of consumers, words that represent extreme emotions, such as exclamation marks, great, excellent, or terrible, awful, are often used (Banerjee & Chua, 2023).

In Moon, Kim, & Iacobucci, (2021) study, linguistic factors were identified by using word patterns to distinguish between fake and real reviews for hotel services. Their research stated that fake reviews have features such as lack of detail, use of present and future tense-oriented language, and emotional exaggeration.

Plotkina, Munzel, & Pallud, (2020) created two separate data pools consisting of fake and real reviews in their research with 1041 people and found that the micro-linguistic automatic detection tool detected fake reviews with 81% accuracy, while the detection rate of humans was only 57%. They noted that this rate remained the same even when fake reviews were given clues to be recognised. The authors emphasised the need for more advanced filtering methods for online consumer review.

Salminen et al. (2022) stated in their research that fake reviews generated by artificial intelligence tools can be detected with very high accuracy using artificial intelligence tools in the same way. They also stated that artificial intelligence can effectively detect not only reviews generated by artificial intelligence tools, but also fake reviews written by humans.

Conclusions

The effects of fake reviews and evaluations on consumer trust in online channels have become an important research topic. This effect is not only limited to individual consumers but also damages the reputation of businesses. Since fake reviews and evaluations do not reflect consumer experiences, they negatively affect consumers' perception of reliability towards businesses and reviews. One of the main reasons why fake reviews significantly affect consumer trust is that they mislead potential buyers by providing false information about a product or service. These reviews do not reflect real experiences and may exaggerate certain features to manipulate consumer perception. Fake reviews also negatively affect the trust in the review system itself. Consumers begin to question the accuracy and reliability of all reviews and ratings, whether real or fake, making it difficult to make informed decisions. This lack of trust can have a negative impact on businesses as they may see a decline in sales and revenue due to sceptical consumers.

These artificially generated reviews and ratings are designed to mimic real consumer sentiments, making it difficult for consumers to detect fake reviews. Indeed, Costa Filho et al., (2023) found that fake reviews are much more likely to go unnoticed by consumers if they are not equipped with the tools to detect them. This manipulation can have serious consequences for consumers, who may purchase low-quality products or services, and businesses, which may experience a loss of trust and reputation.

In addition to AI-generated reviews, there are also cases where businesses hire people or agencies to write fake reviews to boost their ratings and attract more customers (Malbon, 2013). These unethical practices deceive consumers and go against fair competition between businesses. Although policymakers and regulators have started to actively address the issue of fake reviews, legal actions against deceivers are complex and challenging due to the inability to identify and identify perpetrators. Therefore, consumers and review platforms should consider taking active steps to filter out deceptive online reviews. For this, both review platforms and individuals should be able to detect opinion spam (Plotkina et al., 2020). Negative fake reviews can damage a company's image and tarnish their brand image, making it difficult for them to attract or retain new customers. Therefore, companies must actively monitor and address fake reviews to protect consumer trust and reputation (Fong, 2010). Negative comments are critical for businesses to identify their weak points and see them as opportunities for improvement. They can continuously improve their business processes by recognising this feedback as a valuable learning opportunity (Öztürk, 2024). On the other hand, consumers should be cautious when relying on online reviews and only make informed decisions after thorough research and evaluation. In this digital age where information is easily accessible, businesses and consumers need to be vigilant and act responsibly to combat the problem of fake reviews. In conclusion, while digital channels offer new opportunities for consumers to make informed purchasing decisions, they also pose challenges with the increasing presence of manipulated reviews. Businesses should prioritise ethical practices and transparency in online marketing to maintain consumer trust and the integrity of digital platforms.

References

Akdeniz, P. C., & Özbölük, T. (2019). Online Yorumların Tüketici Satın Alma Kararına Etkisi: Kullanıcı Özellikleri Açısından Bir Değerlendirme. *İşletme Araştırmaları Dergisi*, *11*(4), 3104–3119.

Algur, S. P., Patil, A. P., Hiremath, P. S., & Shivashankar, S. (2010). Conceptual level similarity measure based review spam detection. *2010 International Conference on Signal and Image Processing*, 416–423. https://doi.org/10.1109/ICSIP.2010.5697509

Alsubari, S., Deshmukh, S., Alqarni, A., Alsharif, N., H, T., Alsaade, F., & Khalaf, O. (2021). Data Analytics for the Identification of Fake Reviews Using Supervised Learning. *Computers, Materials & Continua*, *70*(2), 3189–3204. https://doi.org/10.32604/cmc.2022.019625

Banerjee, S., & Chua, A. Y. K. (2023). Understanding online fake review production strategies. *Journal of Business Research*, *156*, 113534. https://doi.org/10.1016/j.jbusres.2022.113534

Bauman, A., & Bachmann, R. (2017). Online Consumer Trust: Trends in Research. *Journal of Technology Management & Innovation*, *12*(2), 68–79. https://doi.org/10.4067/S0718-27242017000200008

Cardoso, E. F., Silva, R. M., & Almeida, T. A. (2018). Towards automatic filtering of fake reviews. *Neurocomputing*, *309*, 106–116. https://doi.org/10.1016/j.neucom.2018.04.074

Costa Filho, M., Nogueira Rafael, D., Salmonson Guimarães Barros, L., & Mesquita, E. (2023). Mind the fake reviews! Protecting consumers from deception through persuasion knowledge acquisition. *Journal of Business Research*, *156*, 113538. https://doi.org/10.1016/j.jbusres.2022.113538

Evans, A. M., Stavrova, O., & Rosenbusch, H. (2021). Expressions of doubt and trust in online user reviews. *Computers in Human Behavior*, *114*, 106556. https://doi.org/10.1016/j.chb.2020.106556

Filieri, R. (2016). What makes an online consumer review trustworthy? *Annals of Tourism Research*, *58*, 46–64. https://doi.org/10.1016/j.annals.2015.12.019

Flanagan, P., Johnston, R., & Talbot, D. (2005). Customer confidence: The development of a "pre□experience" concept. *International Journal of Service Industry Management*, *16*(4), 373–384. https://doi.org/10.1108/09564230510614013

Fong, A. (2010). The influence of online reviews: Case study of TripAdvisor and the effect of fake reviews. *Journal of Digital Research and Publishing*, *6*, 106–113.

Hassan, R., & Islam, Md. R. (2021). Impact of Sentiment Analysis in Fake Online Review Detection. *2021 International Conference on Information* *and Communication Technology for Sustainable Development (ICICT4SD)*, 21–24. https://doi.org/10.1109/ICICT4SD50815.2021.9396899

He, S., Hollenbeck, B., & Proserpio, D. (2022). The Market for Fake Reviews. *Marketing Science*. (world). https://doi.org/10.1287/mksc.2022.1353

Hussain, N., Turab Mirza, H., Hussain, I., Iqbal, F., & Memon, I. (2020). Spam Review Detection Using the Linguistic and Spammer Behavioral Methods. *IEEE Access*, *8*, 53801–53816. https://doi.org/10.1109/ACCESS.2020.2979226

Karaca, Ş., & Gümüş, N. (2020). Tüketicilerin Online Yorum Ve Değerlendirme Puanlarina Yönelik Tutumlarinin Online Satin Alma Davranişlarina Etkisi. *Sakarya İktisat Dergisi*, *9*(1), 52–69.

Lee, J., Park, D., & Han, I. (2011). The different effects of online consumer reviews on consumers' purchase intentions depending on trust in online shopping malls. *Internet Research*, *21*(2), 187–206. https://doi.org/10.1108/10662241111123766

Ma, Y. J., & Lee, H.-H. (2014). Consumer responses toward online review manipulation. *Journal of Research in Interactive Marketing*, *8*(3), 224–244. (world). https://doi.org/10.1108/JRIM-04-2013-0022

Malbon, J. (2013). Taking Fake Online Consumer Reviews Seriously. *Journal of Consumer Policy*, *36*(2), 139–157. https://doi.org/10.1007/s10603-012-9216-7

Mathews Hunt, K. (2015). Gaming the system: Fake online reviews v. consumer law. *Computer Law & Security Review*, *31*(1), 3–25. https://doi.org/10.1016/j.clsr.2014.11.003

Mohawesh, R., Xu, S., Tran, S. N., Ollington, R., Springer, M., Jararweh, Y., & Maqsood, S. (2021). Fake Reviews Detection: A Survey. *IEEE Access*, *9*, 65771–65802. https://doi.org/10.1109/ACCESS.2021.3075573

Moon, S., Kim, M.-Y., & Iacobucci, D. (2021). Content analysis of fake consumer reviews by survey-based text categorization. *International Journal of Research in Marketing*, *38*(2), 343–364. https://doi.org/10.1016/j.ijresmar.2020.08.001

Öztürk, İ. (2024). Bodrum Da Faaliyet Gösteren 5 Yildizli Konaklama İşletmelerinde Çevrimiçi Tüketici Yorumlarinin Duygu Analizİ. *Journal of Gastronomy Hospitality and Travel (JOGHAT)*, *7*(2), 397–405. https://doi.org/10.33083/joghat.2024.409

Park, S., & Nicolau, J. L. (2015). Asymmetric effects of online consumer reviews. *Annals of Tourism Research*, *50*, 67–83. https://doi.org/10.1016/j.annals.2014.10.007

Plotkina, D., Munzel, A., & Pallud, J. (2020). Illusions of truth—Experimental insights into human and algorithmic detections of fake online reviews.

Journal of Business Research, *109*, 511–523. https://doi.org/10.1016/j.jbusres.2018.12.009

Ross, L. (2020, May 31). Sahte İncelemelerin Durumu – İstatistikler ve Trendler [2025]—Invesp. Retrieved 1 March 2025, from https://www.invespcro.com/blog/fake-reviews-statistics/

Sahut, J. M., Laroche, M., & Braune, E. (2024). Antecedents and consequences of fake reviews in a marketing approach: An overview and synthesis. *Journal of Business Research*, *175*, 114572. https://doi.org/10.1016/j.jbusres.2024.114572

Salminen, J., Kandpal, C., Kamel, A. M., Jung, S., & Jansen, B. J. (2022). Creating and detecting fake reviews of online products. *Journal of Retailing and Consumer Services*, *64*, 102771. https://doi.org/10.1016/j.jretconser.2021.102771

Schindler, D., & Decker, R. (2013). Some Remarks on the Internal Consistency of Online Consumer Reviews. *Australasian Marketing Journal*, *21*(4), 221–227. https://doi.org/10.1016/j.ausmj.2013.08.001

Song, Y., Wang, L., Zhang, Z., & Hikkerova, L. (2023). Do fake reviews promote consumers' purchase intention? *Journal of Business Research*, *164*, 113971. https://doi.org/10.1016/j.jbusres.2023.113971

Sop, S. A., Atasoy, F., & Günaydin, Y. (2024). Resort Otellerde Çevrim İçi Yorum Manipülasyonu. *GSI Journals Serie A: Advancements in Tourism Recreation and Sports Sciences*, *7*(1), 16–31. https://doi.org/10.53353/atrss.1302316

Utz, S., Kerkhof, P., & van den Bos, J. (2012). Consumers rule: How consumer reviews influence perceived trustworthiness of online stores. *Electronic Commerce Research and Applications*, *11*(1), 49–58. https://doi.org/10.1016/j.elerap.2011.07.010

Wu, Y., Ngai, E. W. T., Wu, P., & Wu, C. (2020). Fake online reviews: Literature review, synthesis, and directions for future research. *Decision Support Systems*, *132*, 113280. https://doi.org/10.1016/j.dss.2020.113280

Zeng, G., Cao, X., Lin, Z., & Xiao, S. H. (2020). When online reviews meet virtual reality: Effects on consumer hotel booking. *Annals of Tourism Research*, *81*, 102860. https://doi.org/10.1016/j.annals.2020.102860

Zhang, D., Zhou, L., Kehoe, J. L., & Kilic, I. Y. (2016). What Online Reviewer Behaviors Really Matter? Effects of Verbal and Nonverbal Behaviors on Detection of Fake Online Reviews. *Journal of Management Information Systems*, *33*(2), 456–481. https://doi.org/10.1080/07421222.2016.1205907

Zhang, H., Chen, D., & Sun, R. (2010). The Study of Consumer Trust in C2C e-Commerce Based on Reputation Score, Information Disclosure, Online Consumer Review Quality. *2010 International Conference on Management of E-Commerce and e-Government*, 184–187. https://doi.org/10.1109/ICMeCG.2010.46

Zhang, W., Du, Y., Yoshida, T., & Wang, Q. (2018). DRI-RCNN: An approach to deceptive review identification using recurrent convolutional neural network. *Information Processing & Management*, *54*(4), 576–592. https://doi.org/10.1016/j.ipm.2018.03.007

Chapter 12

Consumer Manipulation With Artificial Intelligence: Dark Patterns and Hidden Techniques

Kadir Deligöz[1]

Abstract

Technological advancements and artificial intelligence (AI)-assisted digital transformation offer significant opportunities to consumers, while at the same time paving the way for the development of manipulative design strategies. Among these strategies, ***'Dark Patterns'*** are deceptive UI/UX (User Interface / User Experience) design techniques that direct users to perform certain actions without their awareness. Artificial intelligence makes these techniques more complex, personalized and effective, thus guiding users' decision-making processes.

Artificial intelligence-supported ***Dark Patterns*** have negative effects on individual and social levels. These techniques undermine consumer autonomy, leading to financial losses, privacy violations, and reduced trust in digital platforms. In terms of social justice, low-income users may be exposed to more hidden costs and dynamic pricing. Therefore, it is crucial to adopt ethical design principles, increase user awareness and strengthen legal regulations. Raising consumer awareness, promoting transparent digital marketing practices and tightening algorithmic controls by regulatory bodies will be critical steps in the fight against Dark Patterns.

Introduction

The digitalization process, together with technological developments, offers unprecedented opportunities to consumers, while at the same time paving the way for the emergence of new manipulation (manipulation, influence, deception) techniques One of the most prominent examples of these techniques is defined as "Dark Patterns", which are used in user

1 Associate Professor, Atatürk University, kadir.deligoz@atauni.edu.tr, ORCID ID: 0000-0003-3247-9223

https://doi.org/10.58830/ozgur.pub710.c3029

interface (UI) design and direct users to perform certain actions with deceptive or manipulative methods Dark patterns are deceptive design strategies designed to manipulate users on digital platforms These strategies can cause users to unwittingly sign up for subscriptions, make unwanted purchases or share personal data Artificial intelligence technologies are increasingly being used to enhance, personalize and scale the effectiveness of these patterns This raises important debates about consumer rights and digital ethics (Ducato & Marique 2018)

In this section, a comprehensive analysis of AI-powered dark patterns will be presented First, the main types of dark patterns and AI integration will be examined, and then the ethical and social implications of these practices will be discussed Legal regulations and technological solutions will also be discussed in detail, and finally, potential future developments will be evaluated This study aims to take an in-depth look at what AI-driven dark patterns are, how they work, their impact on consumers and the measures that can be taken against them

1. The Concept of Dark Patterns

Today, as digital transformation accelerates, consumers are increasingly engaging with online platforms and digital services. These interactions are largely realized through interface designs that shape the user experience. However, it is observed that these designs do not always serve for the benefit of the user, on the contrary, they can be used for manipulative purposes. These manipulative design patterns, called "dark patterns" or "dark patterns" in Turkish, are defined as insidious tactics that direct users to make decisions against their own interests (Brignull & Darlo, 2019).

Dark patterns are deceptive elements that are intentionally crafted to make the users do actions that they wouldn't do otherwise. Those techniques are used for the benefit of various stakeholders and are included in web products that are used world-wide, such as social media platforms, some popular apps or web services. The concept is well known among practitioners (Cara, 2019: 105). With the development and proliferation of artificial intelligence technologies, the effectiveness and sophistication of dark patterns has also increased significantly. Machine learning algorithms are able to develop personalized manipulation strategies by analyzing user behavior, thereby guiding consumers more effectively (Zhang et al., 2021). Dark patterns tactics are user interfaces that benefit an online service by leading consumers to make irrational decisions they might not otherwise make (Narayanan et al., 2020) or tricking or manipulating consumers into purchasing products or services (Federal Trade Commission, 2022). This raises serious concerns about digital ethics and consumer rights, and calls for new regulations in this area.

2. Historical Development of Dark Patterns

Dark patterns are defined as manipulative design strategies that direct users to perform certain actions. This concept was first introduced in 2010 by User Experience designer Harry Brignull, who drew attention to the ethical risks of such design patterns (Brignull, 2010). Brignull systematically categorized dark patterns and emphasized the aspects of these practices that negatively affect the user experience. Therefore, Brignull's contribution to the concept is important.

With the development of digital platforms, the use of dark patterns has become more sophisticated and widespread, especially in electronic commerce, social media and mobile applications. In this process, machine learning and artificial intelligence-supported algorithms analyze user behavior to develop personalized manipulation strategies and increase the impact of dark patterns.

Understanding the history of dark patterns helps us better understand how these techniques have evolved and their impact on user experience. Table 1 below provides a detailed overview of the development and milestones of dark patterns.

Table 1. Historical Process of Dark Patterns

Year	Milestone	Description
1990s	**The Emergence of Digital Manipulation**	Early e-commerce platforms, such as Amazon and eBay, introduced basic manipulative techniques, including targeted product placements, dynamic pricing, and early-stage pop-up ads (Nielsen, 1994; Wilson, 1997).
2000s	**Privacy Policy Complexification & Hidden Consent Strategies**	Websites began implementing complex, lengthy privacy policies that obscured data collection practices, making it easier for users to give implicit consent (Cranor, 2000). Subscription traps and forced continuity techniques also became more prevalent.
2010	**Introduction of the Term "Dark Patterns"**	UX researcher **Harry Brignull** coined the term "Dark Patterns" and categorized deceptive UI/UX tactics on his website *darkpatterns.org* (now *deceptive.design*) (Brignull, 2010).
2012-2015	**Expansion of Dark Patterns in Social Media & Mobile Apps**	Social media algorithms and mobile apps began integrating dark patterns, such as manipulative notifications, in-app purchase traps, and personalized engagement techniques (Gray et al., 2018).
2016-2019	**AI-Driven Dark Patterns & Algorithmic Manipulation**	The rise of artificial intelligence enabled highly personalized dark patterns. Machine learning algorithms began predicting user behavior, optimizing engagement tactics, and reinforcing compulsive digital habits (Anderson et al., 2020).
2018	**Regulatory Intervention: GDPR & Consumer Protection Debates**	The European Union's **General Data Protection Regulation (GDPR)** took effect, addressing dark patterns related to privacy, data transparency, and user consent (European Commission, 2018).
2020s	**Ethical Design, Legal Reforms & AI Transparency Debates**	Growing awareness of AI-driven manipulation prompted legal and ethical discussions on banning deceptive practices. Countries and regulatory bodies introduced laws against dark patterns in digital marketing (Federal Trade Commission, 2022; Zuiderveen Borgesius, 2018).
2023 & Beyond	**Future Directions: AI Ethics & Transparent User Experience**	Ethical design principles and AI transparency guidelines emerged to counteract dark patterns. Researchers and policymakers continue to advocate for fair, user-centric digital environments (Weinberg, 2018).

The development of dark patterns started with the spread of the internet and the birth of e-commerce platforms, and became more complex with the development of digital marketing techniques. Combined with artificial intelligence and big data analytics, algorithmic manipulation techniques have become increasingly effective. Important milestones in this process can be summarized as follows;

1990s: First Traces of Techniques - The Beginning of Digital Manipulation

With the widespread use of the Internet, online commerce platforms have started to develop strategies to influence users' purchasing behavior. Pioneering e-commerce sites such as Amazon and eBay have transferred product placement, price display and promotion techniques used in traditional retailing to the digital environment (Nielsen, 1994). The manipulation techniques that emerged in this period are as follows:

- Ensuring that users see specific products with product placement algorithms,
- Offering different prices to different user groups with dynamic pricing strategies,
- The first pop-up ads were developed to direct users' attention to specific actions (Wilson, 1997).

2000s: Complexification of Privacy Policies and Commercial Use of User Data

With the rapid spread of the Internet, users' data privacy has become an increasingly big issue. Websites and digital service providers have developed complex privacy policies that allow users to give unconscious consent to collect personal data (Cranor, 2000). In this period;

- User agreements and privacy policies were made long and complex, allowing users to give consent without careful reading.
- "Forced continuity" and subscription traps have been developed to make it easier for users to sign up for services while making the cancellation process more difficult.

2010: Emergence and Systematization of Dark Patterns

Harry Brignull introduced the concept of dark patterns into the literature and began to systematically analyze such manipulative design strategies. He established the website darkpatterns.org (now updated as https://www.deceptive.design/) and contributed to raising awareness (Brignull, 2010). During this period, common examples of dark patterns include:

- "Roach Motel" strategies are methods that allow users to subscribe easily and make it difficult to unsubscribe,

- "Privacy Zudging" techniques, interface designs that encourage users to share more data,

- "Social Proof" manipulations are strategies that encourage users to imitate the behavior of others.

2012-2015: Spread of Dark Patterns and the New Era of Digital Marketing

The rapid growth of social media platforms and mobile applications has enabled dark patterns to reach a wider user base. In particular, personalized recommendation systems and algorithms have been used more effectively to direct users to specific content (Gray et al., 2018). During this period;

- Dark patterns became widespread in mobile apps (e.g., in-app purchase traps).

- Social media algorithms have developed manipulative strategies to ensure that users are exposed to certain content.

2016-2019: Artificial Intelligence Assisted Algorithmic Manipulation

Machine learning and artificial intelligence have led to more advanced techniques for predicting and guiding user behavior. Algorithms that analyze user data have started to create personalized dark patterns strategies at the individual level (Anderson et al., 2020). The prominent developments in this period are as follows;

- Dynamic pricing strategies started to be optimized according to individual purchase history.

- Algorithmic content recommendations included guidance mechanisms that encouraged users to spend more time.

2020 and Beyond: Legal Regulations and Ethical Debates

The proliferation of dark patterns has necessitated the development of legal regulations to protect user rights. Regulations such as the European Union General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) aim to limit dark patterns (Zuiderveen Borgesius, 2018).Today:

- Ethical design and transparency requirements are on the agenda.

- Laws have been developed to protect consumer rights.

- User awareness has increased and platforms containing dark patterns have been criticized.

Dark patterns have become more complex with the development of the internet and digital commerce, and have evolved into personalized manipulation techniques with artificial intelligence-supported algorithms. Although legal regulations and ethical design principles aim to limit these manipulations, the increasing sophistication of artificial intelligence leads to the emergence of new types of dark patterns.

3. Types of Dark Patterns and Artificial Intelligence Integration

Dark patterns are manipulative design strategies that direct users to perform certain actions without their awareness. These strategies usually target the weak points of human psychology and aim to prevent conscious decision-making processes. Today, artificial intelligence is being used to make these manipulative techniques more effective, analyzing user behavior and developing tailored manipulation strategies. Below, we examine common types of dark patterns in the literature and how AI optimizes these patterns.

3.1. Privacy Zudging

Privacy undermining is a type of dark pattern that relies on encouraging individuals to share their personal data or manipulating them into unconsciously giving up their privacy rights. This strategy involves design techniques and persuasion methods that induce users to unwittingly share more data. Social media platforms, e-commerce sites, and mobile apps use methods such as making default privacy settings less protective, presenting permission requests in ambiguous language, or deliberately complicating the process of changing privacy settings to carry out this manipulation (Böhm, 2018).

Artificial intelligence uses various algorithms to make privacy mitigation techniques more effective and personalized. Behavioral analysis, timing optimization, and personalized persuasion strategies are among the frequently used methods in AI-assisted privacy manipulation.

- ***Behavioral Analysis:*** By analyzing users' privacy preferences, previous decisions, and sensitivities, AI algorithms can determine which privacy settings certain individuals are more sensitive to. This analysis enables the creation of personalized manipulative strategies.

- ***Personalized Persuasion***: Customized privacy policies or persuasive messages are offered based on the user's profile and past interactions. For example, a social media platform may display tailored and emotionally-charged alerts to encourage a user to change their privacy settings.

- ***Timing Optimization:*** Artificial intelligence analyzes user behavior to determine the optimal moment to ask for privacy permissions. For example, privacy consent requests can be shown when the user is busy or making a purchase, increasing the likelihood that the user will accept without paying attention to the details.

Facebook's facial recognition feature can be examined from the perspective of privacy undermining. The messages Facebook uses to enable facial recognition are considered an example of AI-assisted privacy undermining. For example, users are presented with a statement such as "Your friends can tag you more easily in photos", aiming to minimize privacy concerns. Such messages encourage individuals to share more data by making the process of changing privacy settings seem user-friendly and advantageous (Waldman, 2020).

As a result, privacy undermining is an ethically controversial manipulation strategy that can lead users to unwittingly violate their right to protect their data. The role of artificial intelligence in this process is to analyze individuals' personal preferences to persuade them at the most opportune moments and develop customized techniques to induce them to share more data voluntarily. This raises serious ethical and legal questions in terms of protecting user privacy and necessitates the tightening of regulatory frameworks.

3.2. Forced Continuity

Coerced sign-up is a type of dark pattern that involves inadvertently steering users into paid subscriptions and deliberately complicating the cancellation process. This usually involves initiating automatic payments after a free trial period, complicating the cancellation process, and developing dynamic strategies that encourage users to continue their subscription. For example, a digital publishing platform may automatically charge users after the trial period expires by requesting their credit card information in advance and deliberately complicate the cancellation process (Følstad, 2020b).

Artificial intelligence uses advanced data analysis methods to make forced registration strategies more complex and effective. Techniques such as predicting user behavior, providing personalized offers, and making the cancellation process harder for the individual are widely used in AI-assisted subscription manipulation (Zuboff, 2019).

- ***Churn Prediction***: AI algorithms analyze previous usage habits and interactions to predict which users tend to unsubscribe. For example, by identifying users who frequently check settings for unsubscribes or who are less interested in content, specific interventions can be planned for them.

- ***Dynamic Retention Strategies:*** AI tries to keep users who tend to unsubscribe by offering them special offers and incentives. For example, a video streaming platform can show a user who wants to unsubscribe a message saying "You got a special 50% discount this month!" or try to keep the user's interest alive by offering special recommendations based on content that the user was previously interested in.

- ***Optimization of the Cancellation Process***: Artificial intelligence can make the subscription cancellation process more complex for the user. For example, some users may be presented with cancellation processes that include more steps, while others may be presented with different screens or distracting surveys such as "Why do you want to cancel your subscription?". At times when the user is impatient or tends to make quick decisions, deliberately lengthening the process may cause them to delay their decision to cancel (Cara, 2019; Coussement, and Van den Poel, 2006; Gkikas, and Theodoridis, 2022).

Research shows that AI-assisted forced persistence techniques cause 67% of users to continue their unwanted subscriptions (Chen et al., 2021). This shows how effective manipulative subscription strategies are and that users tend to continue their subscriptions without realizing it. In particular, services that initiate automatic payments at the end of the trial period, platforms that require users to contact a customer representative at certain hours to cancel subscriptions, or user interfaces that hide cancellation buttons are examples of forced registration techniques.

In digital broadcasting platforms, we can see forced recording manipulation supported by artificial intelligence. In particular, video streaming platforms use artificial intelligence to personalize unsubscribe processes and offer suggestions that encourage users to continue their subscription. When a user tries to unsubscribe before completing a movie, the system may display messages such as "Your subscription will remain active until you complete the content you are watching" as a strategy to delay the cancellation process.

As a result, forced sign-up strategies are an ethically questionable way of deliberately manipulating the user experience in order to keep people subscribed. Artificial intelligence makes these processes more effective by analyzing users' habits and weaknesses, and creates personalized challenges for individuals when unsubscribing. This situation raises important debates in terms of consumer rights, ethical design and digital marketing principles, and is among the issues that regulatory authorities should carefully address.

3.3. Social Proof

Social proof is a psychological and social phenomenon wherein people copy the actions of others in an attempt to undertake behavior in a given situation (Wikipedia, 2025). The peer pressure technique takes advantage of consumers' tendency to follow the decisions of their social circles to encourage them to take certain actions. For example, an e-commerce platform can influence users' purchasing decisions with statements such as "1000 people have bought this product" or "One of your friends liked this product". Artificial intelligence-supported systems analyze individuals' social networks and offer personalized content and recommendations, thereby increasing social pressure and strengthening the tendency to purchase (Cialdini, 2009). This strategy is commonly applied through the following methods.

- ***Popularity Indicators***: By using phrases such as "1000 people have bought this product" or "500 people have made a reservation in the last 24 hours", users develop a positive perception of the product or service.

- ***Friend Recommendations***: By showing users that their friends have purchased a certain product or used a service, social network pressure is created.

- ***Real-Time Notifications***: Notifications such as "Elanur just bought this ticket!" or "10 people are currently reviewing this hotel" encourage users to make quick decisions (Convertize, 2025; Deceptive Design, 2025).

Today, many online shopping sites offer dynamic recommendations that show which products similar users have purchased using an AI-powered system that triggers peer pressure. For example, when a user wants to buy a particular book, the system will suggest other products with the statement "Users who bought this book also bought this book". This technique influences the user's individual decision-making process and creates the perception that "If people like me are buying it, it's probably a good choice".

Digital movie streaming sites have developed recommendation systems that emphasize popular content, especially by using artificial intelligence-supported algorithms. They utilize social proof principles by showing users messages such as "This series is currently the 5th most watched content in Turkey" or "Your friends have watched this content". Furthermore, when the user wants to cancel their subscription, the system can encourage them to continue their subscription by increasing the social proof effect with messages such as "Don't miss the most watched content this month!".

Peer pressure strategies are a powerful manipulation technique based on the principle that people make decisions under the influence of their social environment. Artificial intelligence makes this process more complex, allowing users to be manipulated through their social circles. While some of these techniques aim to improve the user experience, they carry risks of personal data misuse and unethical manipulation. When consumers are unconsciously manipulated into making a purchase decision or encouraged to use a service under social pressure, it is necessary to question the ethical limits of these techniques. Adopting transparency and ethical design principles in the digital marketing world and developing legal frameworks to protect users from deceptive or manipulative manipulation is of great importance.

3.4. Scarcity Principle

The scarcity principle is a type of dark pattern that forces users to make quick decisions by creating the perception that products or services are limited. Human psychology tends to perceive scarce resources as more valuable and desirable. Therefore, digital platforms use scarcity strategies to accelerate users' rational decision-making processes, forcing them to make hasty purchases or reservations (Nodder, 2009). This technique is particularly common in electronic commerce, hotel booking sites and ticketing platforms. Users are shown messages such as "Last 2 rooms left!", "This product is about to run out of stock!" or "10 people are currently looking at this ticket!" to make a quick and impulsive purchase decision.

Artificial intelligence uses advanced data analysis methods to reinforce the sense of scarcity and manipulate users' decision-making process. These techniques are as follows:

- ***Dynamic Scarcity Perception:*** By analyzing the user's previous searches, past purchase data and location information, AI can create personalized scarcity messages. For example, a hotel booking site may show the message "90% occupancy is now reached!" to a user who has previously searched for a hotel in a specific city, but this message may be different for another user.

- ***Real-Time Scarcity Simulation:*** AI algorithms can optimize scarcity messaging by analyzing the amount of time a user spends looking at a particular product and page interactions. For example, when an airfare search site notices that a user has looked at a flight several times, it can show the message "Last 3 tickets left!", thus making the user hurry.

- ***FOMO (Fear of Missing Out) Triggers:*** By taking advantage of users' "fear of missing out" (FoMO) psychology, the perception of scarcity is increased by informing them that other users have already purchased the product. For example, a fashion e-commerce site shows messages such as

"20 people have bought this product in the last 15 minutes!" to help the consumer make a quick decision.

- ***Fake or Exaggerated Stock Information:*** By analyzing the past behavior of the user, artificial intelligence can present stock information in a personalized manner. For example, when an online shopping platform notices that a particular user frequently makes price comparisons, it can display the message "Only 1 product left at this price!", thus enabling the user to make a quick purchase decision (Kim et al., 2023; Deceptive Design, 2025).

Booking websites, in particular, use scarcity tactics to speed up users' accommodation search processes by using artificial intelligence algorithms. When a user enters a hotel page, messages such as "Last 2 rooms left!" or "50 people booked this hotel today!" are displayed.

AI-powered scarcity strategies are a powerful manipulation tool that uses consumer psychology to help users make quick decisions. Unlike in real scarcity situations, these strategies put users under pressure, causing them to make unnecessary or hasty purchasing decisions. Raising consumer awareness of these manipulative techniques and forcing platforms to provide transparent inventory information can create a fairer digital trading environment against scarcity illusion tactics (Cialdini, 2009).

3.5. Hidden Costs

Hidden costs are a type of dark pattern that manipulates consumers by exposing them to additional fees, taxes or service charges that they did not initially see during the purchase process. This strategy is particularly prevalent in online shopping platforms, airline ticketing systems and subscription-based services. It is used to deliberately steer the decision-making process by exposing the user to additional costs that are not predetermined during the purchase process (Weinberg, 2018). For example, on an online shopping platform, the price of the product is attractively displayed, but at the checkout stage, shipping fees, transaction fees or additional taxes are added. In another example, an airline may initially offer a low-priced ticket, but then add additional costs such as seat selection, baggage allowance or transaction fees later in the ticketing process.

By analyzing users' price sensitivity, purchase history and payment trends, AI can dynamically determine which hidden costs to apply to which customers. This may result in some customers facing more hidden costs, while others may see different discounts.

Artificial intelligence-assisted hidden cost manipulation is realized through the following methods:

- ***Price Sensitivity Analysis:*** Artificial intelligence analyzes a user's past purchase data to determine how price sensitive they are. Customers with less price sensitivity may be charged more hidden costs, as they are predicted to be more inclined to complete the transaction.

- ***Dynamic Pricing:*** By analyzing the user's geographic location, previous shopping habits and browsing history, different surcharges can be displayed for each customer. For example, a customer who has previously shopped in the luxury category may be charged a higher shipping fee.

- ***Timing and Buying Psychology:*** Adding surcharges at the last stage, when the user is most likely to make a purchase, can reduce the likelihood of changing the purchase decision. For example, hidden costs can be added to users who are shopping during a sale period, as they are less likely to cancel the purchase because they think they've already gotten a deal.

- ***Cross-selling and Adding Additional Fees:*** Once users are in the buying process, "additional services offered with this product" can be offered to increase the total price unnoticed. For example, a user buying an airplane ticket is told that "it is recommended that you buy extra baggage allowance with this ticket", thus gradually increasing the additional fees (Deceptive Design, 2025; Binns, 2018).

Hidden costs are a manipulative technique that weakens the consumer's control over the shopping process and is becoming more complex with artificial intelligence. When faced with hidden costs, users are often manipulated into accepting additional charges rather than returning, thus making them spend more.

3.6. Roach Motel (Cockroach Motel) Technique

The Roach Motel technique is a type of manipulative dark pattern that allows users to easily sign up for services or subscriptions, while deliberately making the cancellation process difficult. The basic logic of this strategy is based on making the user's entry process simple and fast, but the exit process complex and cumbersome. It is widely used especially in subscription-based services, digital platforms and applications that require membership (Brignull, 2010). The most common applications of this technique are as follows:

- ***Easy online registration, but complex cancellation procedure***: While signing up for a gym membership or digital streaming service can be done in a few clicks, canceling can only be done through a phone call to customer service, visiting the office at certain hours, or filling out lengthy forms.

- ***Intentionally hiding or redirecting the cancel button***: The user may have to navigate through multiple menus and sub-pages to find the cancel option. For example, when trying to cancel a subscription, messages such as "Are you sure you really want to cancel?" or "Keep your subscription to continue enjoying special offers" may appear.

- ***Applying psychological pressure to get the user to back down:*** Users who want to unsubscribe are shown phrases such as "You will lose these great benefits!" or "Most users are happy with our service, why are you leaving?" to create indecision (Deceptive Design, 2025).

By analyzing users' tendency to cancel, AI develops personalized strategies to get them to postpone their decision or abandon the cancellation process altogether. These techniques aim to keep the user connected to the service by making the cancellation process more difficult:

- ***User Behavior Analysis:*** Artificial intelligence algorithms can predict which users are inclined to cancel. For example, users who have not used the service for a long time or who have changed their payment methods may be perceived as more likely to cancel, and specific intervention strategies can be implemented for these people.

- ***Personalized Persuasion Messages***: By analyzing the user's previous behaviors and interests, artificial intelligence can present the most appropriate messages to persuade them. For example, when a music listening platform notices that the user's favorite artist has just released a new album, it can say "Your favorite artist's album will be released soon! Don't cancel your subscription!".

- ***Deliberately Prolonging the Cancellation Process***: When the user wants to cancel, AI-powered systems can guide them through a multi-step process. For example, a digital publishing platform may require the user to fill out a questionnaire during the cancellation process, so that the user may get tired and leave the process halfway through.

- ***Last Minute Special Offers:*** When AI algorithms realize that a user is about to complete the cancellation process, they can offer them a special discount. For example, "You just received a 50% discount! Do you want to continue canceling your subscription?" (Deceptive Design, 2025).

Some online movie streaming and music streaming platforms try to keep users on the service by deliberately complicating the unsubscribe process.

For example: The user may have to click through multiple submenus to find the cancel option. When the user tries to cancel, they may be presented with special discount offers or suggestions for future content. At the final stage, additional steps such as "Please fill out a survey before canceling your membership" can be added to prolong the cancellation process.

To counter this manipulative tactic, it is crucial that more transparent consumer policies are developed, users are made aware of their rights, and digital service providers adopt ethical design principles. Making users more aware of such manipulations and applying to regulatory bodies when necessary will be one of the most effective defenses against unethical marketing strategies such as Roach Motel.

3.7. Bait and Switch

Bait and switch is a type of manipulative dark pattern that lures users to take a certain action by tempting them with an attractive offer, but results in a worse option being offered later in the process instead of the promised one. This strategy, which is based on deliberately misleading consumer expectations, is widely used in various digital domains, especially e-commerce, financial services, subscription-based platforms, and mobile applications (Gray et al., 2018).

While traditional bait-and-switch techniques target the general user audience, artificial intelligence makes this process much more personalized and offers manipulative content based on users' individual tendencies.

AI-powered bait and switch strategies include the following:

- ***Behavioral Data Analysis:*** By analyzing users' past shopping habits, price sensitivities and interests, AI can identify the most attractive offers that will attract them the most.

- ***Dynamic Content Manipulation***: AI can show attractive offers or discounts when a user logs into the platform, only to remove them at the point of purchase and offer higher prices. For example, an airline ticket platform may show the ticket the user is looking for at a low price at the first login, but claim that the price has increased later in the purchasing process, allowing the user to make a quick decision.

- ***Customized Alternative Presentation:*** When it is determined that the user wants to buy a specific product, AI-powered systems can direct them to a more expensive alternative by indicating that stocks are out of stock or the discount period has expired.

- ***Timing and Urgency Manipulation:*** By detecting the moments when the user tends to make urgent decisions, AI can create a manipulative time pressure with messages such as “Don’t miss this opportunity!”.

An online shopping site may announce a campaign such as “Big discounts! Deals up to 70%!”. However, when the user visits the site, it may turn out that the actual discount rates are much lower or that the most demanded products have been excluded. The user is attracted to a service with a free trial period, but later in the process may be hit with mandatory subscription fees or unexpected additional costs.

Dark patterns are strategies that manipulate the user experience and direct individuals’ conscious decision-making processes. Artificial intelligence increases the effectiveness of these techniques, analyzing user behavior more precisely and taking the manipulation to a personalized level. This situation poses a significant problem in terms of consumer rights and ethical debates and reveals the need to update regulatory frameworks and raise awareness (Brignull, 2010; Gray and Kou, 2021; Deceptive Design, 2025).

4. Ethical and Social Implications of Artificial Intelligence-Powered Dark Patterns

AI-driven dark patterns stand out as manipulative design strategies that undermine consumers’ autonomy, freedom of choice and privacy. Digital platforms use artificial intelligence algorithms to analyze user behavior, influence individuals’ decision-making processes and direct them to perform certain actions. These manipulative approaches have important consequences not only on an individual level, but also on social and ethical dimensions (Zuiderveen Borgesius, 2018). We can summarize these consequences as follows:

- ***Declining Trust in Digital Platforms:*** As users encounter misleading and manipulative experiences, they may lose trust in digital platforms and online services. In the long run, this can undermine customer loyalty in the e-commerce, digital media and online service sectors (Koops, 2018).

- ***Impacts on Digital Literacy:*** When users are unwittingly exposed to manipulative strategies, they may struggle to understand how to act in the digital world. This can undermine their ability to use the internet responsibly and safely.

- ***Damage to Social Justice:*** AI-powered dark patterns can increase social and economic inequalities. For example, some consumers may be subjected to dynamic pricing strategies, while individuals with lower income levels may face higher prices. Such practices are contrary to the principles of fairness and equality in terms of consumer rights.

AI-driven dark patterns raise serious ethical concerns, violating users' rights and influencing individuals' decision-making processes through manipulation (Bostrom, 2019). From an ethical perspective, the problems that these applications may create are as follows:

- ***Invasion of Privacy***: By analyzing users' online behavior, AI algorithms can identify their weakest moments and use this information for manipulative purposes. Users' consent without knowing exactly what data is being collected and how it is being used points to an unethical data management process.

- ***Restriction of Consumer Freedom:*** AI-powered dark patterns can disrupt users' rational and informed decision-making processes, causing them to suffer economically and psychologically. Deliberately restricting individuals' freedom of choice should be considered an unethical practice.

- ***Normalization of Manipulation:*** The proliferation of AI-assisted manipulation techniques may lead to the normalization of manipulative user experiences. This may lead to social acceptance of systems that unconsciously manipulate users' decisions.

The fight against dark patterns requires a multifaceted approach. Raising consumer awareness, adopting ethical design principles, establishing legal regulations and developing technological solutions are of great importance in this struggle.

In this context, consumer awareness raising activities can be carried out first. Consumers' knowledge about dark patterns will enable them to recognize these manipulative techniques and act consciously against them. Digital literacy trainings and public awareness campaigns can play an important role in this regard.

In addition, having ethical design principles will enable consumers to have a more transparent and fair user experience. User-friendly privacy settings and clear information processes should be implemented instead of techniques such as "Privacy Thinning".

Legal regulations together with ethical design principles can limit dark patterns (European Commission, 2020). In particular, banning manipulative practices that do not obtain the explicit consent of the consumer, forcing digital platforms to increase their transparency policies, and auditing and criminalizing unethical algorithms are among the measures that can be taken on these issues.

Conclusions And Recommendations

While the process of digitalization and the rapid development of artificial intelligence technologies provide many advantages by personalizing the user experience, they also offer new tools for consumer manipulation. Manipulative design strategies, referred to as dark patterns, are deceptive techniques that lead users to unconsciously perform certain actions. Today, AI-powered dark patterns have become more sophisticated and effective, leading to negative consequences such as forcing consumers into subscriptions, encouraging them to share their personal data, leading them to unwanted purchases, and causing financial losses.

The ethical and social consequences of dark patterns jeopardize the credibility of the digital ecosystem. These AI-powered manipulative practices reduce trust in digital platforms, cause consumers to suffer economic losses, and violate individuals' personal privacy. In addition, the creation of personalized manipulations using artificial intelligence algorithms causes especially low-income individuals to be more at risk. For all these reasons, consumer rights need to be protected, ethical design principles need to be adopted, and regulatory frameworks need to be strengthened.

Consumers, designers, regulators and technology companies have a shared responsibility to minimize the harms of dark patterns. The following measures should be taken to create a more conscious, ethical and transparent digital ecosystem against these manipulative techniques:

Ø ***Consumer Awareness and Increasing Digital Literacy***

One of the most effective measures against dark patterns is to raise consumers' awareness and digital literacy. If users can recognize which manipulative techniques they are exposed to and make informed decisions, the effectiveness of such strategies will decrease.

Ø ***Adoption of Ethical Design Principles and Transparency in UX/UI Practices***

In order to prevent the spread of dark patterns, ethical design principles should be adopted and transparency policies should be implemented in UI/UX. Digital platforms should prefer transparent and user-friendly designs instead of techniques that manipulate user experiences.

Ø ***Strengthening Legal Regulations and Establishing Audit Mechanisms***

In order to bring dark patterns in line with ethical and fair trade rules, consumer protection laws need to be developed and regulators need to conduct effective audits.

*Ø **Establishing Ethical Standards for Artificial Intelligence Developers***

To prevent the proliferation of AI-enabled dark patterns, AI developers should fulfill their ethical responsibilities and create user-friendly algorithms.

*Ø **Detecting and Preventing Dark Patterns with Technological Solutions***

New technological solutions should be developed and offered to consumers in the fight against dark patterns.

Artificial intelligence-supported dark patterns are manipulative techniques that undermine consumers' free will and pose serious ethical problems. In the fight against such practices, it is critical to raise consumer awareness, adopt ethical design principles, establish legal regulations, ensure that artificial intelligence developers fulfill their ethical responsibilities, and prevent these manipulations with technological solutions. All stakeholders need to take responsibility to create a more fair, transparent and ethical digital ecosystem.

References

Anderson, J., Sarma, K. M., & Borning, A. (2020). Deceptive Design. *Communications of the ACM*, 63(10), 126-133.

Binns, R. (2018). Fairness in machine learning: Lessons from political philosophy. *Proceedings of the 2018 Conference on Fairness, Accountability, and Transparency,* 149–159. https://doi.org/10.1145/3278721.3278722

Bostrom, N. (2019). *Süper zekâ: Yapay zekâ uygulamaları, tehlikeler ve stratejiler* (F. B. Aydar, Çev.). Alfa Yayıncılık. (Orijinal eser 2014'te yayımlanmıştır)

Böhm, K. (2018). Privacy by Design. *In: Encyclopedia of Big Data Technologies*. Springer, Cham.

Brignull, H. (2010). Dark patterns: Deception vs. honesty in UI design. Dark Patterns. Retrieved January 10, 2025, from https://darkpatterns.org/

Brignull, H., & Darlo, C. (2019). *The Dark Patterns Tip Sheet*. Retrieved from https://darkpatterns.org/

Cara, C. (2019). Dark patterns in the media: A systematic review. *Network Intelligence Studies*, 7(14), 105.

Chen, L., Lee, K., & Nissenbaum, H. (2021). Bias in Algorithmic Transparency. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW1), 1-32.

Cialdini, R. B. (2009). *Influence: Science and practice*. Pearson Education.

Convertize. (2025). Social proof & dark patterns: How marketers manipulate consumers. Convertize. Retrieved January 7, 2025, from https://www.convertize.com/social-proof-dark-patterns/

Coussement, K., & Van den Poel, D. (2006). Churn prediction in subscription services: An application of support vector machines while comparing two parameter-selection techniques. Expert Systems with Applications, 34(1), 313–327. https://doi.org/10.1016/j.eswa.2006.09.038

Cranor, L. F. (2000). Internet privacy. *Communications of the ACM*, 43(9), 29-31.

Deceptive Design. (2025). Dark Patterns. Retrieved February 7, 2025, from https://www.deceptive.design/

Ducato, R., & Marique, E. (2018). Come to the dark side: We have patterns. Choice architecture and design for (un)informed consent. Choice Architecture and Design for (Un) *Informed Consent*.

European Commission. (2018). *General Data Protection Regulation* (GDPR).

European Commission. (2020). *Shaping Europe's Digital Future*. Retrieved from https://ec.europa.eu/digital-single-market/en/shaping-europes-digital-future

Federal Trade Commission. (2022). Available at: Bringing dark patterns to light. Assessed on September 26, 2022 https://www.ftc.gov/reports/bringing-dark-patterns-light.

Følstad, A. (2020a). Dark Patterns in UX Design. In: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. ACM.

Følstad, A. (2020b). What do users consider as dark patterns?. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (pp. 1-14).

Gkikas, D. C., & Theodoridis, P. (2022). AI in consumer behavior. In Advances in artificial intelligence-based technologies (Chapter 10). Springer Cham. https://doi.org/10.1007/978-3-030-80571-5_10

Gray, C. M., Kou, Y., Battles, B., Hoggatt, J., & Toombs, A. L. (2018). The Dark (Patterns) Side of UX Design. In: Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. ACM.

Gray, C., & Kou, Y. (2021). "The Ethics of Dark Patterns in UX Design." *Journal of Business Ethics*, 169(3), 425-440. doi:10.1007/s10551-020-04443-3.

Kim, K. (K.), Kim, W. G., & Lee, M. (2023). Impact of dark patterns on consumers' perceived fairness and attitude: Moderating effects of types of dark patterns, social proof, and moral identity. Tourism Management, 98, 1–14. https://doi.org/10.1016/j.tourman.2023.104763

Koops, B. J. (2018). The Concept of Privacy in the Digital Age. In: Proceedings of the 2018 International Conference on Information Systems. AIS.

Narayanan, A., Mathur, A., Chetty, M., & Kshirsagar, M. (2020). Dark patterns: Past, present, and future: The evolution of tricky user interfaces. ACM Queue, 18(2), 67–92.

Nielsen, J. (1994). Usability engineering. Morgan Kaufmann. https://www.nngroup.com/books/usability-engineering/

Nodder, C. (2009). Evil by Design: Interaction Design to Lead Us into Temptation. Wiley.

Waldman, M. (2020). Privacy as Trust. Cambridge University Press.

Weinberg, B. D. (2018). The Dark Side of UX Design. In: Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. ACM.

Weinberg, G. (2018). Dark patterns in the design of digital interfaces.

Wikipedia. (2025). Social proof. Wikipedia, The Free Encyclopedia. Retrieved March 7, 2025, from https://en.wikipedia.org/wiki/Social_proof

Wilson, B. (1997). The Annoying Pop-Up Ads.

Zeller, W. (2014). Mobile application usability. Morgan & Claypool.

Zhang, Y., & Liu, Z. (2021). The Addictive Nature of Social Media. Journal of Computer-Mediated Communication, 26(5), 325-342.

Zuboff, S. (2019). *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*. New York: Public Affairs.

Zuiderveen Borgesius, F. J. (2018). Dark Patterns in the Digital Economy. In: Proceedings of the 2018 International Conference on Information Systems. AIS.

Chapter 13

Social Responsibility and Ethical Approaches in the Management of Artificial Intelligence

Nesibe Kantar[1]

Abstract

Artificial intelligence, whose technological foundations were laid by the end of the 20th century, is on the one hand progressing towards taking away the intellectual competence of human beings, and on the other hand, it is redesigning our lives from production to marketing, from health to our cultural acquisitions. Unlike the traditional, the restructuring process is most felt in the field of culture and values. While the economic and commercial success that artificial intelligence has demonstrated in the field of production and marketing satisfies our desire to earn and produce more, on the other hand, ignoring human-centered ethics in societies, institutions or communities that do not use technology or do not have advanced artificial intelligence technologies can cause a number of ethical problems. Regardless of its purpose or field, the use of artificial intelligence in line with ethical responsibility and ethical principles in a way that will contribute to the ethical development and progress of humanity is not only a matter of a society or community, but of all humanity. It is an unethical situation known to everyone that marketing activities or technology producing companies manipulate the actions and activities of the end user. On the other hand, the unethical sharing of user information by social media companies with other organizations or companies regarding the special vulnerabilities or needs of individuals, and the violation of data privacy have made the use of ethical artificial intelligence one of the most important issues in the world of informatics. Every private or legal entity in the production-distribution segment of companies must assume ethical responsibility in their actions. This study first presents a historical perspective with the aspects that brought artificial intelligence, the strongest argument of the informatics revolution, to the present day. Secondly; ethical concepts and methods that can help in coping with social and ethical difficulties caused by non-human factors such

1 Dr. Öğretim Üyesi, Kırşehir Ahi Evran Üniversitesi, nesibekantar@hotmail.com, ORCID ID: 0000-0003-3179-2314

https://doi.org/10.58830/ozgur.pub710.c3030

as robots, softbots and artificial intelligence devices in the informatics society are explained. All economic activities, including local or global marketing, of artificial intelligence, which has the potential to shape the development of the world, should be shaped according to ethical needs by focusing on humans. Finally, the study draws attention to the importance of human-centered trustworthy artificial intelligence in the context of social responsibility.

1. An Overview at Artificial Intelligence from the Information Revolution

The information revolution refers to the period in which technology was designed with information, cybernetics and technology studies after the Industrial Revolution, and at the same time information was designed and produced with technology. Norbert Wiener's Cybernetics (1948), Claude Shannon's Information Theory (1949), and developments in computer technologies in the late 19th and early 20th centuries are the characteristic disciplines of the information revolution.

In the beginning, electronic computers were large and cumbersome because they used many vacuum tubes. The development of valves (valves that provide electronic flow) in the 1960s and transistors supported by integrated circuits and microprocessors in the 1970s brought computers to an ergonomic structure. Improvements in integrated circuits and silicon chip technologies have made it easier to use computers almost everywhere.

The impact of the information revolution has been realized on the widest scale worldwide with the hypertext transfer protocol http (*Hyper Text Transfer Protocol*), which is designed to receive, transmit and display data. The World Wide Web (WWW) was developed in 1989 and became official with the protocol signed at CERN (Kizza, 2017: 8). The effect of the information revolution has deepened by eliminating the space constraints of access to information resources such as online music, digital health, internet television, digital telephone, digital communication systems, e-shopping, and e-government through the internet, which allows the creation of a virtual atmosphere parallel to physical reality by connecting to each other via internet protocols (TCP/IP). Our world has become increasingly globalized with the Internet, the World Wide Web, which represents the infrastructure where all devices and servers are connected to each other, and the social, cultural and economic impact of the information revolution.

Norbert Wiener, one of the founders of ***cybernetics***, and his colleagues developed a computerized calculation method that tracked fighter planes in the air and predicted the trajectory of enemy aircraft during World War

II. (Bynum , 2000). The opportunities provided by cybernetic studies that enable communication between human-machine and machine-machine have initiated the "automatic age", as the term used to refer to unmanned systems (Bynum, 2009: 25-48). The ethical discussions of automata and intelligent systems were also initiated by Wiener during the rise of cybernetic studies (Wiener, 1960).

Cybernetics is undoubtedly one of the most important developments of the information revolution. Cybernetics is the branch of science that establishes the law of communication that is equally valid for living beings and machines (Porush, 1987: 54). Cybernetics is a discipline that enables interaction between humans, machines and society through control and communication theories. (Ashby, 1956: 1). As seen in Figure 1, thanks to Cybernetics, data and information from different branches of science such as biology, physics, mathematics, social sciences and engineering are integrated to produce a new output. In addition to the interaction of living and non-living systems, cybernetics, as a surveillance and control system, is an important actor in the scientific information revolution and an important milestone in the point where artificial intelligence technologies have reached.

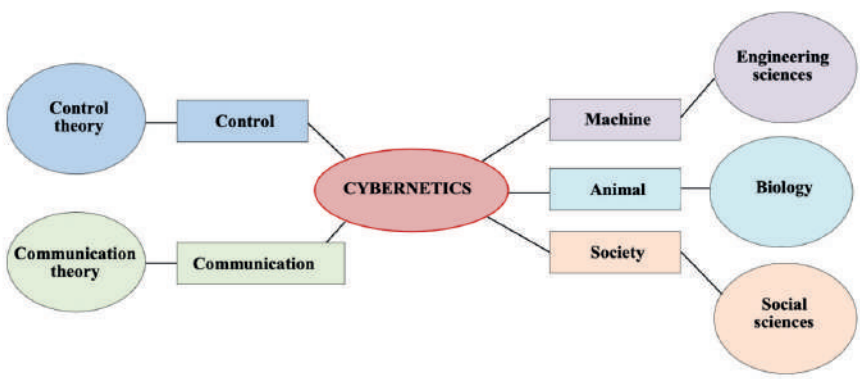


Figure1. Fundamentals of Cybernetics. (Novikov, 2016: 10)

Claude Shannon's "**Information Theory**" constitutes the architectural structure of the information revolution technically, where data transmission is carried out as a portable type between the message receiver and transmitter via telephone wires, TV cables, radio signals and digital computers (Shannon, 1948: 2).

Quinn defines all devices that enable the creation, storage, processing, exchange and distribution of data, audio or images through information technologies as the actors of the information revolution (Quinn, 2006: 39). A strong reflection of this revolution today is artificial intelligence technologies.

Artificial intelligence is one of the popular technologies that the technologies developing with the information revolution have brought to our agenda. Although artificial intelligence is defined in different ways, it is possible to define artificial intelligence in its most well-known form as the integration of the ability to learn and solve problems related to all kinds of acquisitions specific to the human species into information technologies and systems. Artificial intelligence refers to the ability of intelligent computational machines with algorithms and mathematical calculations to perform tasks of human intelligence in a human-like manner.

AI technologies simulate cognitive functions such as solving problems, learning for expected output, understanding language that enables communication between human-machine and machine-machine, and creative thinking with data and data sets. Techniques such as machine learning, deep learning, and natural language processing constitute the basic elements of artificial intelligence. Figure 2 shows the basic working logic of AI.

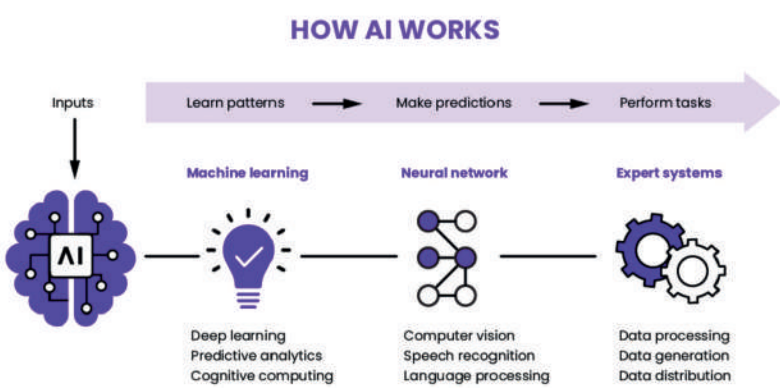


Figure 2. How AI Work. (Weka.io, 2024)

Although artificial intelligence refers to a technical field, it has a complex structure that cannot be attributed to a single branch of science. In fact, the main purpose of artificial intelligence is to solve problems without focusing on a specific field. AI, which is a mental activity that distinguishes humans from other beings in terms of being a thinking being, focuses on the problem itself with algorithms and mathematical models and carries out different optimizations for the solution of this problem with human-like experience acquisitions. It is closely related to different branches of science and disciplines, from philosophy to biology, from mathematics to marketing and business. Because the central concept in artificial intelligence is knowledge. As in other positive sciences and social disciplines. In its most primitive definition, the data is modeled with different methods such as machine learning, natural language processing, expert systems in the stages it passes through as input-process and output.

The development stages of AI systems begin with Data collection, which is the data collection phase that takes place through sensors or human-generated sources to train and evaluate the AI model. The collected data is processed, classified and cleaned by field experts in the Feature engineering stage with statistical analysis or automatic feature selection techniques to be used in the training of the artificial intelligence model in the Data preprocessing stage. The AI model architecture and algorithm for the relevant field are selected according to the problem-oriented statistical models, machine learning algorithms or deep learning architectures, and the determined model is trained using the prepared data in the Model development phase. In the model evaluation and model optimization stages, studies are carried out to develop and improve the model created (Weka, 2024).

Although the emergence of artificial intelligence in its modern form, inspired by the structure and functions of the human brain, dates back to the 1956s, the earliest research on machines being able to think was developed through the collaborative work of scientists specializing in different fields in the late 1930s, 1940s and 1950s. In fact, its foundations were laid at the Macy Conferences moderated by McCulloch, titled "Circular Causal and Feedback Mechanisms in Biological and Social Systems" between 1946 and 1948 (Pias, 2016: 12). In neuroscience research, the definition of the brain as an electrical network of neurons has brought about the artificial modeling of the human brain. Norbert Wiener's cybernetics and Claude Shannon's theory of information have made it possible to describe digital signals. Alan Turing showed with his theory of computation that any computation could be described digitally. All these ideas suggested that it might be possible to design an "electronic brain". In the process, these studies were brought to the agenda again at the Dartmouth conference and in the summer of 1956 under the leadership of scientists such as Marvin Minsky, John McCarthy and Carnegie-Mellon, Allen Newell and Herbert Simon, a new science-technology field called artificial intelligence took its current form (McCorduck, 20024; 51-57).

In 1950, Alan Turing developed a study that tested the ability of a machine to exhibit intelligent behavior equivalent to a human with the 'imitation game theory'. Turing's study adapted natural language speech to a human-like communication model between machine and machine (Turing,1950). Turing's study, which adapted the electronic brain model to human spoken language, took artificial intelligence to a different dimension and made him one of the pioneers of today's artificial intelligence studies. The scope and foundations of artificial intelligence are composed of expert systems for solving data-related problems, robotics, natural language processing technologies based on speech and understanding that enable machine communication, optical instrument technologies that are independent of physical interaction, computer vision that includes data perception, collection and classification activities, machine learning, and deep learning models produced by artificial neural networks by creating more than one artificial neural network. Artificial intelligence, which realizes human-specific abilities such as learning and problem solving through information technologies, has played an important role in producing meaningful results through algorithms aimed at solving inputs from large data sets, as well as in the optimization of existing ones and the emergence of new inventions.

The information revolution has affected our social life, habits, and also our scientific and thought methods. The philosophy of artificial intelligence is one of these. Through new technologies, it has caused us to reconsider human life and scientific methods, the nature of intelligence and reason, which are the characteristics that distinguish us from other beings, their limits, our consciousness, moral concepts such as will, decision-making, and freedom, and to reach different philosophical conclusions with new definitions. The philosophy of artificial intelligence, which addresses the ethical, epistemological, ontological and social dimensions of artificial intelligence technology, has brought to the philosophical field the issue of whether a machine can have consciousness, the possibility of ethical decisions with machines, and the effects of developing a technical solution to technology-based ethical problems on human nature. This study, which addresses ethical problems in the ecosystem where artificial intelligence technologies, which are the subject of the current study, are created and ethical approaches to solving these ethical problems, is the result of such an impact.

2. Ethics Responsibility For The Information Society

During the Second World War, and almost immediately thereafter, several powerful information technology advancements were made. After that, during the 1950s and later decades, information technology advanced rapidly. By the mid 1990s, worldwide use of the Internet had already produced major impacts upon political, social, and economic circumstances. More and more people found themselves living in a "cyber-world" created and sustained by a vast network of interconnected digital devices. The world today has become a place with innumerable inter-cultural interactions, and the "Information Age" has arrived.

Today, whether they like it or not, nearly everyone is becoming a member of the worldwide "cyber-community". So, in the comfort of their own specific culture, without traveling in a car or train or airplane, people can easily interact with other people in many different cultures. Because of this, the "Information Revolution" is changing traditional habits and generating new and profound ethical questions and challenges. For example: Are there common ethical values and principles shared by all human beings, or does each specific culture or subculture have its own ethical values? To address such questions, *an effective ethical theory for living in a massively interconnected multicultural world is needed!* One such theory is Flourishing Ethics put forward by American philosopher Terrell Ward Bynum in 2006 (Bynum, 2006). The most important feature of this theory is that humanity assumes the responsibility for the ethical development of the individual and society.

Because the first important responsibility that individuals and society should undertake in their commercial activities or daily work should be to flourish ethically. The most important mission of artificial intelligence technology manufacturers and other smart technologies should be to strengthen, support or provide opportunities for the ethical flourishing of humans. Focusing on the benefits of a technology only in terms of economic activities and evaluating it based on measurements related to this will deficient the ethical flourishing of humans and society, so the responsibility for ethical development should be at the core of technologies. Indeed, The power of any technological product, be it artificial intelligence or whatever its name, is directly proportional to the ethical responsibility it assumes.

Let's take a closer look at the theory that addresses human flourishing as a kind of ethical responsibility in societies designed with artificial intelligence and intelligent computational technologies.

Bynum's Flourishing Ethics Theory includes both Human-Centered Flourishing Ethics and General Flourishing Ethics. This theory is an "umbrella-like" overarching conception of ethics, which is broad enough to include not just traditional Western values and principles—like those of Virtue Theory, Utilitarianism, Deontology, and Social Justice Theory—but also values and principles of major Eastern traditions like Buddhism, Confucianism, and Taoism. According to this theory, social responsibility in the point of view of ethics is a significant concept in the technological societies.

In addition to providing a means of ethically evaluating human actions, Flourishing Ethics also can be used to guide and govern decisions and actions of newly-emerging nonhuman agents like robots, softbots, and AI devices that are currently being created and deployed in many different societies. If nonhuman agents contribute to human flourishing, and they do not also damage human flourishing, and if these technologies take on the responsibilities of individuals and societies for ethical development, they can be considered as appropriate or useful tools for use.

Of course, Flourishing Ethics is not a panacea that can easily answer all ethical questions in our increasingly complex interconnected world. The important point here is that it provides promising and powerful ethical concepts and methods to help with a growing number of social and ethical challenges of the Information Age.

2.1. What is Flourishing Ethics as an ethical theory with potential for ethical perspective on artificial intelligence and social responsibility?

In his article "Flourishing Ethics", Bynum said this:

I call the new theory 'Flourishing Ethics' because of its Aristotelian roots, though it also includes ideas suggestive of Taoism and Buddhism. In spite of its roots in ancient ethical theories, Flourishing Ethics is informed and grounded by recent scientific insights into the nature of living things, human nature and the fundamental nature of the universe—ideas from today's information theory, astrophysics and genetics. . . . Rather than replacing traditional 'great ethical theories,' Flourishing Ethics is likely to deepen and broaden our understanding of them (Bynum, 2006, p. 157).

Bynum's Flourishing Ethics assumes that *people in every culture share a common human nature*, and also that *human flourishing is the highest ethical value*. These assumptions, taken together, yield a set of ethical values and principles that apply to every human being in every culture. In addition, since individual cultures and subcultures typically include *culture-specific* values and traditions, human flourishing within a given culture can depend also upon the culture-specific values of that culture. So Bynum's Flourishing Ethics accommodates culture-specific values when they do not harm human flourishing elsewhere.

To determine what is required for humans to flourish, Bynum adopted the strategy of asking this question: *For all humans, what deficiencies would make it impossible for them to flourish?* The results were these (see Kantar and Bynum 2022):

1. **Autonomy**—the ability to make significant choices and carry them out—is a necessary condition for human flourishing. For example, if someone is in prison, or enslaved, or severely pressured and controlled by others, such a person is not flourishing.
2. To flourish, people need to be included in **a supportive community**. Knowledge and science, wisdom and ethics, justice and the law are all social achievements. Also, psychologically, humans need each other to avoid loneliness and feelings of isolation.
3. The community must provide—at least reasonably well—**security, knowledge, oppor-tunities, and resources**. Without these, a person might be able to make choices, but nearly all of the possible choices could be bad ones, and a person could not flourish under those conditions.
4. To maximize flourishing within a community, **justice must prevail**. Consider the traditional distinction between "distributive justice" and "retributive justice": if goods and benefits are unjustly distributed, some people will be unfairly deprived, and flourishing will not be maximized. Similarly, if punishment is unjustly meted out, flourishing, again, will not be maximized.
5. **Respect**—including **mutual respect between persons**—plays a significant role in creating and maintaining human flourishing. Lack of respect from one's fellow human beings can generate hate, jealousy, and other very negative emotions, causing harmful conflicts between individuals—even wars within and between countries. **Self-respect** also is important for human flourishing in order to preserve human dignity and minimize the harmful effects of shame, self-disappointment, and feelings of worthlessness.

2.2. General Flourishing Ethics, "smart" technology, and emerging global ethics

In the article Flourishing Ethics, Bynum made the following important prediction:

Flourishing Ethics has a significant potential to develop into a powerful 'global ethics'—one that is rooted in the ultimate nature of the universe and all the entities that inhabit it—one that will shed new light upon 'the great ethical theories' of the world, while providing novel insights and contributions of its own (Bynum 2006, p. 171).

A helpful contribution of Bynum himself was his recognition that Flourishing Ethics should be broadened and divided into two "types": The first type is *Human-Centered Flourishing Ethics*, which recognizes the dignity and worth of human beings as the top ethical values. The second type is *General Flourishing Ethics*, which continues to keep human worth and dignity at the top, but also acknowledges the *intrinsic ethical value* of other existing entities. Such broadening of ethical respect actually began to occur years ago with developments like the environmental ethics movement, the animal rights movement, efforts to limit global warming, and so on.

Bynum's ethical explanations and analyses are informed and grounded by recent scientific insights into the nature of living things, human nature and even the fundamental nature of the universe—ideas from today's information theory, astrophysics and genetics. As a result, his "broader view" is this:

From the point of view of Flourishing Ethics, it is not unreasonable to place a strong emphasis upon the flourishing of human beings and their societies. . . . On the other hand, besides humans and their communities, there are other intrinsically good entities in the universe. . . . Flourishing Ethics takes these into account as well. Non-human animals, plants, ecosystems, even certain machines decrease entropy in their local regions of space-time, and thereby preserve and increase the good. Even 'inert' objects like stones, mountains, planets, stars and galaxies are persisting patterns of Shannon information. [So] Flourishing Ethics fosters respect for all of these sources of the good (Bynum 2006, p. 172).

Of special interest in today's world is the growing number and complexity of information technology devices like robots, softbots, and chatbots. Such devices sometimes make decisions and carry them out without human intervention. At the present time people worldwide are especially concerned about artificially intelligent chatbots, which can learn from their "experiences" and change their behavior in unexpected ways.

3. Ethical Responsibility and Management of Artificial Intelligence

The agent factor is a very important factor in the collaboration activities that multiple artificial intelligence technologies come together to achieve a goal. For example, in the ecosystems that form artificial intelligence collaborations, who will be authorized to use the data, the unauthorized use of data by other parties, the limitations to be applied to data manipulation, etc., and who will assume the ethical responsibility of the system in solving these issues and problems are quite controversial issues.

There are views that argue that ethical responsibilities should be shared by users in a common way regarding who should assume the ethical responsibilities of artificial intelligence and what and according to what principles it should be governed. Indeed, in ecosystems created by more than one artificial intelligence, machines should make joint decisions and cooperate on actions. Being in the same ecosystem also means sharing responsibility. According to Stahl, who advocates a shared responsibility model in the artificial intelligence ecosystem, sharing responsibility among different actors such as software developers, users, and institutions (Stahl, 2023) is necessary for ethical outcomes to be undertaken.

One of the important issues here is that the agents in the AI ecosystem are designed according to the purpose of the ecosystem. The components in the AI ecosystem develop together for the same purpose and feed off each other (Ritala and Almpanopoulou, 2017: 39-40). The data that is the output of one system can be the input of another system. This can be a strength of complex AI management, but it can also be a source of social and ethical problems.

Ultimately, although artificial intelligence models are produced for economic purposes such as commercial, educational or marketing, they produce social, ethical and cultural results as individuals determine and influence society's actions. For this reason, the management of artificial intelligence systems and the ecosystem they build is extremely vital in terms of social responsibility, not just economic importance.

4. Trustworthiness in the Management of Artificial Intelligence and Human-Centered AI

Despite criticisms about the technique used by machine learning in the processing stage of data, the transparency and bias produced by the methods and producing wrong answers, Artificial Intelligence is one of the most important technical developments of the century that has the potential to shape the future of the world. This potential will produce a result depending on whether we create AI in what degree that contributes to the development of humanity. This vital issue is still waiting as a problem waiting to be solved on the table of all humanity. For this reason, all studies investigating ethical problems and seeking solutions in artificial intelligence studies are an important effort on behalf of humanity. The issue of AI and ethics does not belong only to a single country or culture, but is the common problem of all humanity in the face of developing technology. The trustworthy of AI and the other problems it produces are a worry for all countries, making it almost imperative to develop minimum common solutions that can be valid on a local and global scale. Since we have common ethical problems with the dimensions that affect us; Why shouldn't it be possible to address issues from a common ethical perspective and seek appropriate solutions by at least meeting on minimum common principles? While this may seem difficult in practice - at least for now - it is not impossible.

There are several controversies in determining AI ethical principles and appropriate ethical statements. At the beginning of these discussions is the application of topics and concepts such as human autonomy, human agency and oversight, Diversity, non-discrimination and fairness. As the application of these principles differs between nations and countries; It is getting harder to reach a consensus on what principles and rules belong to the culture, belief and law that are expected to be integrated into AI should be. According to what and how should nations act in establishing AI ethical principles?

There are ethical declarations different from each other for the development of trustworthy AI technologies, which creates a controversial issue.

These and other questions regarding the development and management of artificial intelligence reveal the necessity of a reliable ethical declaration that is accepted by everyone and contributes to the ethical development of humans. It is clear that artificial intelligence management that is not transparent or does not promise the use of models that can be explained to the parties will lack ethical sensitivities. The correct and ethical application and management of artificial intelligence models that prioritize the ethical development of humans by focusing on humans and ensuring the reliability of data will affect the commercial, cultural and all activities of the information society (European Commission).

Conclusion

Artificial intelligence systems consist of codes and hardware designed and written by humans to achieve a purpose. They are systems that can receive thousands of highly complex data from the external environment, redesign the data they have and change its form, collect and analyze visual, auditory and textual data. More than one artificial intelligence can come together for a similar purpose to form a system, this large environment is called the artificial intelligence ecosystem.

In the ecosystem created by artificial intelligence systems, new data can be obtained, as well as reinterpretation of structured data. These activities are important for processing data and making optimal decisions on data.

Although artificial intelligence has technical achievements such as machine learning, symbolic processing, image processing, it is an interdisciplinary field with a priority on social responsibility since it is the work of modeling human actions (Stahl and friends,2020).

In artificial intelligence systems, it is an extremely important issue that the model product should prioritize human development in an ethical context beyond its economic benefit. In artificial intelligence and ecosystem, regardless of the product output, human ethical development should be at the center. The components of the Flushing ethical theory as ethical responsibility in artificial intelligence management are therefore explained in detail in the study. It is an issue that everyone agrees on, without a doubt, that non-human-centered technologies will harm the organic structure of the individual and society. The ethical development of humans should be the main concern of state administrators and policy makers as a social responsibility. As a matter of fact, as we explained the evolution of artificial intelligence in the first section, technology is developing more and more rapidly and expanding its scope of application. This makes it difficult to manage artificial intelligence and its ecosystems.

Trustworthy artificial intelligence design in artificial intelligence management will contribute to the ethical flourishing of humans. In the context of social responsibility, the use of human life should not be left to machine reasoning alone, and this should be formulated with ethical principles and rules and interdisciplinary practices.

Companies that use artificial intelligence, including marketing, need to be aware of the impacts they create on society. Ecosystems designed with ethical approaches are needed to create a sustainable and fair marketing strategy.

References

Aristotle (2009). *On the Movement of Animals; On the Soul: Nicomachean Ethics;* and *Eudemian Ethics.*

Ashby, W. R. (1956). “An Introduction to Cybernetics”. John Wiley and Sons. https://doi.org/10.5962/bhl.title.5851

Bynum, T. W. (2006). “Flourishing Ethics”, *Ethics and Information Technology,* Vol. 8, No. 4, pp. 157-173.

Bynum, T. W. (2009). Milestones in the History of Information and Computer Ethics. In: Kenneth E. Himma and H.T. Tavani (eds). The Handbook of Information and Computer Ethics. 1st ed. New Jersey, John Wiley & Sons Ltd. 25-48.

Bynum, T.W. (2000). A Very Short History of Computer Ethics. The Research Center on Computing & Society. https://www.cs.utexas. edu/~ear/cs349/Bynum_Short_History. html. 02. 08. 2024.

European Commission-Ethics Guidelines for Trustworthy AI | Shaping Europe’s Digital Future. (2019, April 8). https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai (01.05.2024)

Kantar, N. and Bynum, T. W. (2021). “Global Ethics for the Digital Age—Flourishing Ethics.” *Journal of Information, Communication and Ethics in Society*, Vol. 19, No. 3, pp. 329– 44.

Kantar, N. and Bynum, T. W. (2022). “Flourishing Ethics and identifying ethical values to instill into artificially intelligent agents.” *Metaphilosophy,* Vol. 53, No. 5, pp. 599-604.

Kizza, J. M. (2017). Ethical and Social Issues in the Information Age. (6th Ed.) Springer International Publishing.

McCorduck, P. (2004). Machines Who Think (2nd ed.), Natick, MA: A. K. Peters, Ltd.

Moor, J. H. (1999). “Just Consequentialism and Computing”, *Ethics and Information Technology*, Vol. 1, No. 1, pp. 61-65. DOI 10.1023/A:1010078828842

Novikov D.A. (2016). Cybernetics: From Past to Future. Heidelberg: Springer.

Pias, C. (2016). Cybernetics: The Macy Conferences 1946-1953. The Complete Transactions, Diaphanes.

Porush, D. (1987). Reading in the ServoMechanical Loop. Berkeley, Calif. Discourse, 1987-04-01, 9: 53-63.

Quinn, M. J. (2006). Ethics for the Information Age. (2nd Ed.). Pearson International Edition Inc.

Shannon, C. E. (1948). A Mathematical Theory of Communication. *The Bell System Technical Journal*, 27(3): 379-423.

Stahl, B. C. (2023). Embedding Responsibility in Intelligent Systems: From AI Ethics to Responsible AI Ecosystems. *Scientific Reports*, 13(1), 7586. https://doi.org/10.1038/s41598-023-34622-w

Stahl, B., Andreou, A., Brey, P., Hatzakis, T., Kirichenko, A., Macnish, K., Shaelou, S., Patel, A., Ryan, M., and Wright, D. (2020). "Artificial Intelligence for Human Flourishing -Beyond Principles for Machine Learning". Journal of Business Research, 124. https://doi.org/10.1016/j.jbusres.2020.11.030

Turing AM (1950) Computing machinery and intelligence. *Mind* 59:433–460

Weka- https://www.weka.io/learn/guide/ai-ml/what-is-ai/ (27.01.2024)

Wiener, N. (1948). *Cybernetics: or Control and Communication in the Animal and the Machine*, Technology Press .

Wiener, N. (1950). *The Human Use of Human Beings: Cybernetics and Society*. Houghton Mifflin. (Second Edition Revised, Doubleday Anchor, 1954.)

Wiener, N. (1960). Some Moral and Technical Consequences of Automation, *Science*, 131: 1355–1358.

Chapter 14

Unrealistic Beauty Ideals: Artificial Intelligence and Consumers' Self-Image Perceptions

Feyza Nur Özkan[1]

Abstract

Digital transformation and the rapid enhancement of artificial intelligence (AI) technologies cause unprecedented changes in the marketing environment. As the technology evolved and AI tools were diversified, AI became more effective in facilitating consumers' lives and was adopted quickly by large masses. While this technology offers numerous opportunities, it also poses a serious threat to consumers' well-being by shaping society's beauty ideals. People judge others according to their appearance, and beautiful-looking people have a competitive advantage. Thus, beauty is perceived as important and highly demanded by consumers due to its influential power. Although beauty perceptions of consumers were culture-dependent and constantly changed throughout history, they have become similar nowadays, with the increase in communication and the effects of globalization.

The unrealistic and unattainable beauty ideals shaped and disseminated by AI may damage consumers' self-image perceptions, fill them up with insecurities, and eventually result in serious health and consumption-related problems. Therefore, this chapter aims to explain AI's role in shaping beauty ideals and AI's adverse effects on consumers' self-image perceptions and intends to contribute to the literature on the dark side of AI in consumers' beauty and self-image perceptions context. This study is descriptive in nature and is guided by the self-theory and social comparison theory. The present study also discusses AI's health-related and consumption-related effects and the mindful use of AI for consumer well-being and building an inclusive society.

1 Ph.D., Istanbul University, School of Business, feyza.kamis@istanbul.edu.tr, ORCID: 0000-0003-1346-3963

https://doi.org/10.58830/ozgur.pub710.c3031

1. Introduction

Digitalization and the advent of artificial intelligence (AI) irreversibly changed how consumers live and perceive the world. This paradigm shift caused remarkable changes in consumer behavior and the marketing landscape. AI has gradually integrated into consumers' lives and finds a place in almost every sphere of life with social media, chatbots, voice assistants, recommendation systems, and Internet of Things (IoT) devices (Barari et al., 2024). As AI technologies evolved and were widely adopted by consumers, their role in enhancing customer experience (Grewal et al., 2023) was discovered by the companies, and more engaging AI technologies such as virtual reality (VR) try-on technologies and augmented reality (AR) face filters were introduced. As digital transformation and AI evolve, the technologies they incorporate offer numerous opportunities in the marketing environment for consumers, companies, and society. However, AI also has a dark side that leads to adverse, harmful, or unintended outcomes for the actors in the marketing environment.

One of AI's significant risks is its potential to negatively affect consumers' self-image perceptions by shaping beauty ideals. AI enables consumers to create and enhance visuals with a few clicks and companies to offer more personalized and engaging customer experiences (Ameen et al., 2021). The image editing tools for self-presentation in the digital world have been diversified and enhanced with the power of AI and quickly adopted by consumers who desire a perfect appearance. However, constant exposure to AI-generated flawless faces and perfect-looking bodies may promote hyper-idealized beauty standards and distort consumers' self-image perceptions by triggering social comparisons.

Desire for beauty and interest in beautiful people is a worldwide and transhistorical phenomenon. Therefore, consumers' desire for a perfect appearance and their effort to conform to society's beauty expectations is not new. Beauty ideals were culture-specific before globalization and the widespread use of web-based technologies. However, increased communication and worldwide adoption of communication technologies have removed the geographical and cultural barriers, and consumers' perceptions of beauty have become similar. Consumers' beauty perceptions are experiential and influenced by the environment (Dimitrov & Kroumpouzos, 2023). Recent reports demonstrated that adult internet users' average time spent online is 6 hours and 38 minutes each day, and they spend 2 hours and 21 minutes of this time only on social media (We Are Social & Meltwater, 2025). Thus, consumers are exposed to beauty content daily on the internet and social media for a considerable amount of time, which is more than enough to shape and change their perceptions of beauty. Related literature demonstrates that consumers' exposure to appearance-oriented content is damaging (Yan & Bissell, 2014) and may cause negative health-related and consumption-related consequences.

AI poses a serious threat to the well-being of consumers by generating and enhancing idealized beauty visuals that may fill consumers up with insecurities. Although consumers' beauty and self-image perceptions in the social media context attracted considerable scholarly attention (e.g., Ando et al., 2021; Fioravanti et al., 2022; Laughter et al., 2023; Xie, 2024), research investigating AI's effect on consumers' self-image perceptions is limited. However, the influence of emerging technologies on consumers' beauty perceptions is a prominent research theme in health sciences and marketing (Singer & Papadopoulos, 2024). Therefore, AI's role in shaping beauty ideals deserves more attention in today's digital landscape.

This chapter aims to explain AI's role in shaping beauty ideals and its adverse effects on consumers' self-image perceptions in light of self-theory, social comparison theory, and previous study findings. In addition, the present study also discusses AI's health-related and consumption-related effects and the mindful use of AI for consumer well-being and building an inclusive society.

2. The Evolution of Beauty Ideals in the Digital Age

Beauty is a complex concept. Due to its subjective nature, no commonly accepted definition exists and is still discussed from philosophical, historical, biological, and social perspectives (Wong et al., 2021). Some scholars argue that it is easier to feel and recognize rather than to describe or define it (Alam & Dover, 2001; Dayan, 2011). Although no clear definition of beauty exists, its effects on our lives are undeniable. People tend to judge others according to their appearance. This phenomenon is known as beauty bias, an attributional bias that indicates positive perceptions toward attractive people rather than unattractive ones (Struckman-Johnson & Struckman-Johnson, 1994). Consumers' beauty perceptions not only affect mate selection but also social interactions and self-esteem (Singer & Papadopoulos, 2024). Beautiful people face fewer difficulties in life compared to ordinary people. For example, they are treated better, employed with higher salaries, and get even less severe punishments than unattractive people, even if they are in the same position or have similar qualifications (Frederick et al., 2015). Therefore, it is unsurprising that consumers try to achieve better looks and conform to society's beauty perceptions and expectations.

According to Georgievskaya et al. (2025), beauty is the combination of attributes that make a person subjectively perceived as aesthetically appealing in a given cultural environment. However, beauty standards have constantly changed throughout history. Early Greeks defined aesthetic perfection with numeric symmetries and proportions (Alam & Dover, 2001). Mayan culture linked beauty to food resources and tried to change their hair and facial structures to look like corn (Frederick et al., 2015). Some cultures valued body fat, while others valued thinness. While pale skin is considered an essential beauty standard in Asian culture, and therefore, consumers are heavily invested in skin-lightening products and medications (Dimitrov & Kroumpouzos, 2023), solarium, skin bronzers, and sun tanning products and services are quite popular and highly demanded in other cultures. Although there were specific differences in beauty perceptions in different cultures in history, global consumer culture has emerged with the irresistible effect of globalization (Cleveland & Laroche, 2007), and the differences in beauty perceptions have blurred. Global consumer culture creates global consumer segments that assign the same or similar meanings to certain things (such as beauty), and differences coming from culture become less important (Alden et al., 1999; Keillor et al., 2001). Therefore, traditional cultural beauty ideals have transformed into international norms through globalization. These beauty standards in mass culture promoted flawless skin, symmetrical faces, slim bodies, youthfulness, and Western looks (Georgievskaya et al., 2025; Grech et al., 2024).

Alongside globalization and global consumer culture, digital technologies have also altered how we perceive the world. Media plays a significant role in this process and acts as a tool for the dissemination of certain beauty ideals throughout the world (Yan & Bissell, 2014). Before the rise of the internet, traditional media forms were dominantly shaping consumers' beauty ideals with celebrities in advertisements, movies, and TV series. The thin ideal was promoted at that time, and below-average weighted female bodies were portrayed in traditional media (Lewallen & Behm-Morawitz, 2016).

After the widespread use of the internet and the popularization of social media, consumers become content creators and producers of images of their own lives. Until the twentieth century, beauty was considered a distinctive characteristic of a closed, prosperous elite beyond ordinary people's reach. However, consumers now have unlimited access to endless ideas to develop tastes, opportunities to be beautiful, and building communities to demonstrate their perceptions of beauty (Kuipers, 2022). This shift caused social democratization, and beauty was also democratized. Body positivity and naturalism have gained momentum, and consumers even criticize brands for using unrealistically perfect-looking models in their advertisements. Leading fashion and personal care brands realized this movement and went one step forward by promoting natural women in their advertisements and launching natural beauty campaigns (Mabry-Flynn & Champlin, 2018). Then, natural beauty trends went viral on social media, and something went wrong. For example, "no-makeup makeup" and "clean girl" trends took social media by storm. These trends seem like minimalist beauty trends, which are effortless and easy to reach for everyone at first glance. However, consumers who follow these trends need to spend remarkable amounts of money on expensive new clothes, cosmetic products, decorative objects, etc. Besides, following these beauty trends demands too much time, which is also not even possible for the majority of working women. As we know, trends come and go; they are only popular for a finite period. Although trends are subject to change, social media's effect on consumers' beauty perceptions stays the same. Thus, even though social media has a prominent role in democratizing beauty, it remains a powerful source of appearance pressure and perpetuates certain beauty ideals simultaneously (Bell et al., 2022).

Digitalization, internet adoption, and social media use have revolutionized consumers' perception and presentation of beauty. When AI was introduced and gained popularity, consumers increasingly integrated it into their daily lives, especially to make their lives easier. Companies also started to use AI when they realized its essential role in shaping customer experience (Ameen et al., 2021). However, despite numerous advantages, AI poses significant risks for shaping consumers' perceptions of beauty and promoting unrealistic beauty ideals, worse than ever in history.

3. AI's Role in Shaping Beauty Ideals

AI's role in shaping beauty ideals can be viewed from three angles: consumer - AI interactions, AI in company-consumer interactions, and algorithmic bias in AI. Consumers and companies may integrate AI into their digital activities with different motives, yet they both contribute to creating and disseminating certain beauty ideals shaped by AI.

Consumer - AI interactions

Social media connected consumers all over the world. Consumers willingly engage in social media and generate content with rational and emotional motives of knowledge-sharing, advocacy, social connection, and self-expression (Krishnamurthy & Dou, 2008). In visual user-generated content, aesthetic concerns arise, and consumers want to leave a good impression on their social connections (Ayar et al., 2025). Consumers' desire to look attractive led them to use image editing tools to beautify their virtual appearance. They used Photoshop at first, but as technology evolved, the tools for altering images became more complex and powerful. Face filters and VR apps have come into play. Identifying altered images with Photoshop was not difficult for trained eyes; however, when AI was involved, it almost became impossible to distinguish whether the content was authentic, AI-touched, or AI-generated by the naked eye (Hashemi et al., 2024).

Consumers may use AI to generate and enhance visual content on social media. AR face filters and VR beauty applications are AI technologies that enable consumers to change their appearance in videos and photographs. These AI-based technologies can be used for makeup, hair color change, face and body touch-ups, beautification such as skin smoothing, skin tone correction, eye and teeth whitening, slimming waist, enlarging breasts, filling lips, etc. Large masses have quickly adopted the aforementioned AI-based technologies, and consumers were increasingly bombarded with more idealized and unrealistic images in social media. Although beauty and body image-related digital activities such as image editing tools enable consumers to alter their faces with just a few clicks, to conform to beauty ideals of society with minimum effort (Castillo-Hermosilla et al., 2023), to generate content for perfectionist self-presentation, constant exposure to this kind of beauty content on social media may trigger consumers' social comparisons and appearance concerns (Boursier et al., 2020). In addition, constant exposure to visual contents containing altered images with AI blurred consumers' perceptions of what is normal, good enough, or perfect (MacCallum & Widdows, 2018). As consumers get used to these images, what was exceptional and outstanding is perceived as normal, and what used to be normal is now perceived as substandard (Kuipers, 2022).

Beauty filters negatively affect consumers' well-being. Prior to the widespread use of AI-face filters, consumers desired to have an appearance like celebrities. However, there is a shift in the desire for an ideal look from celebrities to one's filtered self (Castillo-Hermosilla et al., 2023). Consumers are now dreaming of resembling and looking like their filtered appearance. This phenomenon was defined and conceptualized as Snapchat Dysmorphia, which causes consumers to lose perspectives on their actual appearance and poses significant risks to consumers' mental health (Ramphul & Mejias, 2018; Abbas & Dodeen, 2022). Figure 1 demonstrates how far AI retouching apps can change a person's appearance.

Figure 1: Real/AI-filtered face comparison

Source: Dove (2021)

AI in company-consumer interactions

Companies may also use AI-generated content in digital marketing communications due to its high potential to attract consumers' interest and cost-effectiveness. However, using AI-generated flawless faces and perfect-looking bodies in brand communications may promote hyper-idealized beauty standards. Companies that aim to enhance customer experience adopted and offered VR try-on technologies, VR beauty applications, virtual models and influencers, AR mirrors, and AR live streaming technologies. VR try-on technologies help consumers to visualize products in a real-world setting. It enables consumers to try makeup (see Figure 2), contact lenses, nail polish, jewelry, and clothes-like products virtually before purchasing. This technology even lets consumers visualize how their appearance will change after undergoing specific plastic surgery with the AI plastic surgery simulator. Although virtual try-on technologies improve customer engagement and shopping satisfaction (Ajiga et al., 2024), they may also negatively affect their perceptions of self-image.

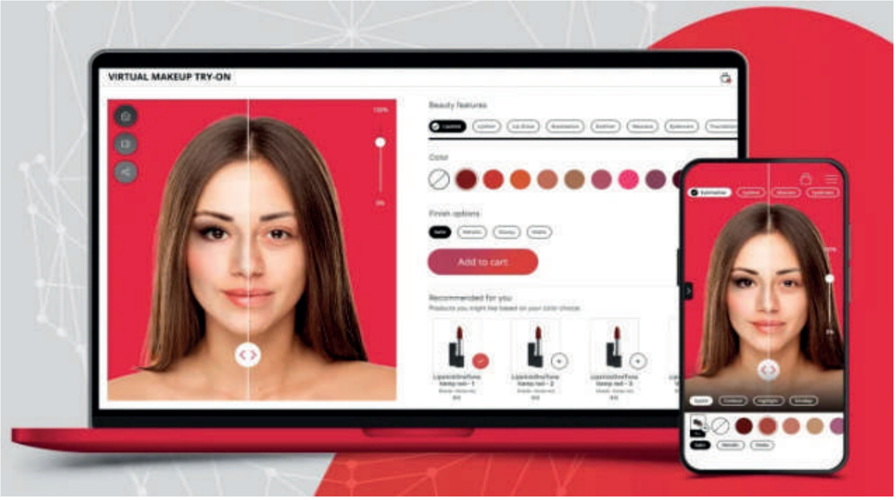


Figure 2: Virtual makeup try-on technology

Source: Androic (2023)

Another AI-enabled technology is virtual models and influencers. Companies may want to employ virtual models and influencers to represent broader consumer segments at lower costs. For example, Levi Strauss & Co (2023) announced their partnership with Lalaland.ai. This company specializes in creating customized AI-generated hyper-realistic models of every body type, size, age and skin tone. One of these AI-generated virtual models can be seen in Figure 3 as an example.

Figure 3: An AI-generated virtual model (Levi Strauss & Co. / Lalaland.ai)

Source: Levi Strauss & Co (2023)

Prada is another company that uses virtual models in digital marketing communications such as Rethink Reality: Prada Candy (Prada, 2021). Prada employed Candy (see Figure 4), an AI-generated virtual model, as an ambassador of their "Prada Candy" fragrance. The previous ambassador of this fragrance was a real human being, a French actress, Léa Seydoux, in 2011. As time passed, the fragrance and its target consumer group (young women) stayed the same. However, the majority of young women are tech-savvy Gen Z nowadays. Thus, Prada decided to change the ambassador with a virtual model and successfully reached its target consumers (Pesonen, 2022).

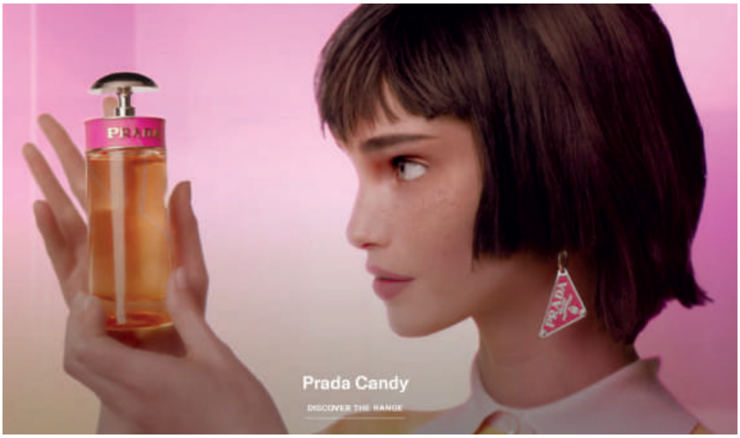


Figure 4: An AI-generated virtual model (Rethink Reality: Prada Candy)

Source: Prada (2021)

LG also uses AI-based technologies. The company has its own virtual influencer named Reah Keem, LG was first introduced her to the public in 2021 (LG, 2021). Reah identified herself as the first virtual artist in Korea and made even her debut as a singer in 2022 (LG, 2022).

Figure 5: A virtual influencer (Reah Keem, LG)

Source: LG (2022)

Although using AI-generated virtual models and influencers has numerous advantages for companies, such as enhanced customer experience, better representation of some consumer groups, cost-effectiveness, and attracting the attention of especially young consumers, its adverse effects should also be considered. Even though AI models and influencers are not real humans, it is nearly impossible to differentiate from real people, especially hyper realistic AI models (see Figure 3). Young consumers find AI models and influencers more relatable (Pesonen, 2022), which means they will compare themselves with these models, and this comparison may fill them up with insecurities, and distort their self-image perceptions. Because real humans cannot have the perfect look that virtual models and influencers always have.

AI-based technologies are not limited to VR try-on technologies, VR beauty applications, virtual models and influencers, AR mirrors, and AR live streaming. Some companies even use AI skin analysis to offer personalized cosmetic and skincare recommendations tailored to the individual skin concerns of consumers. AI skin analysis includes image processing algorithms and deep learning models that use previously collected consumer data for training. Algorithm bias-related issues raise concerns about the underrepresentation of specific consumer groups and marginalize their skin conditions, appearance, and ethnicity-specific differences (Grech et al., 2024). This kind of AI-based technology also promotes skin-related beauty trends in social media, such as "glass skin," which is actually a term used to describe glass-like smooth, flawless, clear, poreless, and shiny skin.

Glass skin is hard to achieve beauty ideal that also demands a considerable amount of time and money. Consumers trying to achieve and maintain this look must invest in a vast amount of skincare products and follow specific skincare routines, which takes a lot of time every day. Another risk of this kind of skin-related beauty trend is promoting a youthful appearance among consumers. Unrealistic expectations regarding youthful appearances may distort consumers' aging-related perceptions and prevent embracing the natural beauty of women of all ages.

Algorithmic bias in AI

Algorithmic bias in AI is also a significant factor in shaping beauty ideals. AI biases related to beauty may arise from algorithmic design, inadequate training, or biased datasets (Grech et al., 2024). Algorithmic bias occurs when an algorithm produces outputs that benefit or disadvantage certain individuals or a group of consumers without justified reasoning (Kordzadeh & Ghasemaghaei, 2022). Although recommendation systems are essential tools for enhancing customer experience in a digital environment (Shokeen & Rana, 2020), AI algorithms may reinforce social biases that already exist in society (O'neil, 2016). AI algorithms learn from data. If the data used in learning an algorithm was lacking cultural diversity, the algorithm cannot generate suggestions including all aspects of different cultures. This may result in the marginalization of diverse beauty representations and reinforce harmful stereotypes. In addition, the algorithm also learns from consumers' behavior (Sethi & Gujral, 2022). For example, recommendation systems in social media generate content offers according to consumers' user profile based on their browsing behavior. If the learning data of the algorithm does not include people who have no hair, then content offers generated by this algorithm do not include images of hairless people.

AI algorithms are engagement-focused and designed to attract consumers' interest. Therefore, when the algorithm is fed by similar visuals, it becomes to recommend similar visual content over time. Then, overspecialization may occur, and consumers become constantly exposed to similar content that lacks diversity (Lashkari & Sharma, 2023). Accordingly, algorithmic bias in AI may disseminate certain beauty trends and cause the idealization of certain face and body characteristics. For example, if a consumer is interested in makeup videos and visuals, the social media algorithm will constantly generate makeup-related content suggestions. When the consumer keeps engaging in suggested content, suggestions will become more particular as a specific makeup trend over time. Another example is when the AI algorithm is learned from the user profile as the consumer likes to see the content include people who have beautified and rejuvenated faces with aesthetic surgery, then all the suggested content will include people who underwent similar aesthetic surgeries and have similar face and body characteristics. As exposure to those contents gets higher, consumers' perceptions of what is normal, good enough, or perfect may become blurred (MacCallum & Widdows, 2018), and consumers may perceive these beauty ideals as attainable and normal, and feel obliged to follow these aesthetic trends to conform society's beauty ideals.

4. AI's Effects on Consumers' Self-Image Perceptions

AI offers numerous advantages for companies and consumers; however, using AI-based technologies and constant exposure to AI-generated content, especially appearance-oriented content, may distort consumers' perceptions of self-image. Although the present study is not an empirical study relying on its very own data, this paper analyzes and discusses the AI's effects on consumers' self-image perceptions in light of the self-theory, social comparison theory, and the previous study findings. Therefore, this section provides theoretical underpinnings of AI's effects on consumers' self-image perceptions. In this vein, self-theory and social comparison theory are defined and discussed in detail.

4.1. Self-Theory

Self-theory is a personality theory mainly focusing on the real self and ideal self (Rogers, 1959). According to theory, self is people's perceptions related to their own characteristics, their perceptions of the relationships with other people and life, and values attached to all these perceptions. The ideal self is a self-concept to which a person attaches the highest value and wants to achieve. Self-concept is a multi-dimensional concept in nature that has various facets. The *real self*, defined as the actual or objective self, indicates who the person really is; *self-image*, as the subjective self, refers to how the person perceives herself/himself; the *ideal self* is self-actualization, who the person would like to be; *social self*, defined as the way the person thinks others regard him/her (Onkvisit & Shaw, 1987). Therefore, we can define self-image as who consumers perceive themselves they are, and the ideal self as who consumers really want to be.

Self-theory is a widely used theory to explain consumer behavior in the marketing literature (e.g., Onkvisit & Shaw, 1987; Ekinci & Riley, 2003; Kressmann et al., 2006; He & Mukherjee, 2007). Marketing research focuses mostly on the actual self and ideal self, especially self-image congruence, which means the cognitive match between consumers' self-concepts (e.g., actual self and ideal self) (Hosany & Martin, 2012). Incongruence occurs if a discrepancy develops between the actual and ideal self. This state is associated with tension and internal confusion, resulting in neurotic behaviors (Rogers, 1959). Similarly, Higgins (1987) defines this concept as self-discrepancy, which occurs when consumers compare different self-states and find discrepancies between the two. According to him, three self-states exist: *actual self*, *ideal self*, and *ought self*. Ought self indicates the attributes a person thinks he/she is obliged to have. These self-concepts would be the person's own perspective or the perspectives of significant others (Vartanian, 2012).

According to self-discrepancy, six types of self-concepts could be experienced: actual/own, actual/other, ideal/own, ideal/other, ought/own, and ought/other (Higgins, 1987). These self-state representations are important due to their motivational significance. When this theory is applied to consumers' beauty and body image perceptions context, actual/own indicates consumers' own perceptions of their body, ideal/own refers to how consumers think their body would ideally like to be, ideal/own indicates consumers' internalization of society's beauty ideals. Consumers' discrepancy perceptions between these self-states may cause serious problems such as dissatisfaction, depression, anxiety, and guilt (Vartanian, 2012). According to MacCallum and Widdows (2018), if the discrepancy between the actual self and the ideal self occurs, consumers feel disappointment and sadness. In addition, the discrepancy between the actual self and the ought self leads to anxiety and guilt.

Appearance-oriented content may affect consumers' ideal self-perceptions and lead to appearance-changing behaviors such as eating disorders by causing actual-ideal discrepancy (Grogan, 2007). In addition, exposure to idealized beauty images may also heighten the discrepancy between the actual and the ought self and may cause restricted eating in public, to be perceived as a person who is trying to conform to society's appearance-related expectations (Hefner et al., 2014; MacCallum & Widdows, 2018). Consumers' food choices may also be affected. In order to give the impression to other people as someone trying to achieve a healthy, fit, and thin appearance, consumers may prefer lower calorie foods in the presence of others. In addition, perceived self-discrepancy between the actual and ideal appearance may cause serious health concerns such as disordered eating, depression, body surveillance, and body dysmorphic disorder (Castillo-Hermosilla et al., 2023).

4.2. Social Comparison Theory

Social comparison theory focuses on the idea that people evaluate their abilities and opinions according to outside images (Festinger, 1954). As the name suggests, social comparison theory indicates an inner drive of people to evaluate and understand themselves in comparison with similar others in a social environment. In today's digital age, this comparison is stronger than ever with the widespread use of social media platforms and the increasing use of AI. Prior to the advent and adoption of web-based technologies, consumers' social surroundings were limited to friends, colleagues, neighbors, and the people they met physically. However, when social media rises, consumers are suddenly exposed to people's lives, appearances, experiences, and thoughts, even from the distant corners of the world. Then, AI came into our lives, and social comparison extends to virtual humans who do not even exist.

Comparison motives of consumers include evaluation, improvement, and enhancement (Gibbons & Buunk, 1999). Social comparison theory helps us understand the motivations of consumers' self-evaluation and improvement and how these motivations shape consumer behavior (Caliskan et al., 2024). According to the theory, comparisons can be made in upward and downward directions (Wills, 1981). The upward comparison refers to consumers' comparison of themselves with superior others; however, the downward comparison indicates comparison with inferiors. AI-generated beauty images and beauty-related content cause upward comparison because these contents are entirely of perfect-looking images that promote and disseminate unrealistic and unattainable beauty ideals. Upward comparison of consumers may result in inadequacy, and envy (Caliskan et al., 2024), and body dissatisfaction when the comparison is made with idealized media images (Tiggemann & Polivy, 2010).

According to Wood (1996), social comparison does not have to be careful or even conscious thought. Comparisons can be made with an image, a person, or a group of people in relation to the self. Therefore, consumers may unconsciously make social comparisons when constantly exposed to AI beauty content on social media. People do not tend to compare themselves with others who have distinctively different abilities or opinions, according to Festinger (1954). When this theory is applied to body image perceptions and ideal beauty context, people do not usually compare themselves with supermodels because the difference is extremely divergent from their own. However, a friend using AI filters, a virtual influencer, or an AI-generated better version of himself/herself can be easily subjected to comparison.

Comparisons may also occur when the attractions of the compared groups are strong. Another reason for comparisons is consumers' desire to stay as a member of a specific group (Festinger, 1954). When considering the advantages of being a member of an attractive group and the adverse effects of not conforming to beauty ideals, comparison is almost inevitable, especially for young women (Yan & Bissell, 2014).

Social comparison research in consumers' beauty perception context demonstrates that women's self-image perceptions negatively change when they perceive the comparison target as extremely attractive (Birkeland et al., 2005; Brown et al., 1992). According to Yan and Bissell (2014), constant exposure to appearance-oriented content, such as extremely thin and unrealistically perfect-looking bodies, is even more destructive for young women. This kind of content may lower consumers' self-esteem and cause body image dissatisfaction, eating disorders, and depression (Harrison & Cantor, 1997; Lavine et al., 1999).

5. AI's Consumption-Related Effects

AI's adverse effects on consumers' self-image perceptions may cause serious health problems as discussed in the previous sections. In addition, AI's adverse effects on consumers' self-image perceptions may also have consumption-related effects. Social comparison theory suggests that consumers try to eliminate the perceived discrepancy when a difference between desired others and perceived self is recognized (Yan & Bissell, 2014). Mandel et al. (2017) introduced compensatory consumer behavior model to explain consumer behaviors in regulating self-discrepancies. The compensatory consumer behavior model suggests direct resolution, symbolic self-completion, dissociation, escapism, and fluid compensation as consumers' strategies for coping with self-discrepancies. In addition to these strategies, this model also suggests that consumption may reduce self-discrepancies.

AI-enhanced visuals include face and body touch-ups, such as face filters changing face features and putting desired makeup on consumers' faces. When consumers are exposed to these AI-enhanced visuals of others without any disclosure of AI use, they cannot define whether the visual is real or AI-enhanced. If AI-generated visuals are known to be artificial, consumers would no longer perceive the image as a comparison target. Therefore, awareness of digital enhancement is expected to cause less social comparisons and less body dissatisfaction (MacCallum & Widdows, 2018). Otherwise, consumers may perceive the content as real and feel insecure about their appearance. In order to reduce this self-discrepancy, consumers' demand for cosmetics, skincare, and beauty products is increasing (Fardouly et al., 2015; Grech et al., 2024; Singer & Papadopoulos, 2024). To reach the desired appearance, consumers' demand for fitness foods, beauty and dietary supplements, and even aesthetic surgery heightens (Yan & Bissell, 2014; Nobile et al., 2023; Krywuczky & Kleijnen, 2024). Although increased demand for beauty products is favorable for the beauty industry, it has detrimental effects on consumers and society. It raises concerns about health issues related to excessive use of skincare or cosmetic products and appearance-related concerns due to the excessive demand for plastic surgery for similar esthetic procedures that transform people into look-alike masses.

6. Conclusion

AI has an undeniably significant role in shaping beauty ideals in today's digital age. Even though AI offers countless benefits, there is a dark side of AI that involves risks. AI's role in shaping beauty ideals can be threefold: consumer – AI interactions, AI in company-consumer interactions, and algorithmic bias in AI. AR face filters, VR beauty applications, VR try-on technologies, virtual models and influencers, AR mirrors, AR livestreaming technologies, AI skin analysis, and algorithmic bias constitute the tools, technologies, and characteristics of AI shaping, perpetuating, and disseminating beauty ideals.

Consumers' discrepancy between the actual self and the ideal self increases when they are constantly exposed to AI-generated beauty content. While these contents damage their self- image perceptions, they also promote almost perfect and unattainable beauty ideals. Even though social comparison theory suggests that when a comparison target is considered irrelevant to the present status, it will not affect the self (Strahan et al., 2006), consumers' perceived difference is not that high from the comparison target when AI is involved. Constant exposure to AI-generated or AI-enhanced visuals causes constant observation of numerous comparison targets, normalizes the perfect-looking bodies, and makes them seem attainable over time. In addition, AI itself also decreases perceived differences from the comparison target because the comparison target is not usually a supermodel; instead, a friend using AI filters, or even consumers' an AI-powered better version of themselves. Therefore, beauty content's adverse effects on consumers are more serious and dangerous than ever before.

The detrimental effects of AI-generated or AI-enhanced visual content on consumers are not limited to the distortion of self-image perceptions.

It also raises serious health and consumption-related concerns. Health-related effects include eating disorders, restricted eating in public, body dissatisfaction, body surveillance, body dysmorphic disorder, and depression. Besides, consumption-related effects include increasing demand for cosmetics, skincare, beauty products, fitness foods and products, beauty and dietary supplements, and even aesthetic surgery.

Even though serious risks are involved, AI is a widely used technology in almost every sphere of life, and we should find a way to minimize the risks while enjoying its advantages. Consumers and companies may integrate AI for their digital activities with different motives; however, considering its consequences is the responsibility of every actor in the marketing environment for the welfare of society. Although AI offers various tools and technologies to make life easier for everyone, responsible use and implementation are key for consumer protection and preventing possible harm. Transparency is also important. Consumers should know whether AI is used to generate or enhance visual content. Awareness of digital enhancement is expected to prevent consumers from unnecessary and irrelevant social comparisons to achieve unattainable and unrealistic beauty ideals. In addition, diversity in beauty should be protected and encouraged for a more inclusive society. Broadening our perspectives of beauty by embracing the beauty of all ages, all body shapes, all skin types, and colors would help to build a more empathetic world.

References

Abbas, L., & Dodeen, H. (2022). Body dysmorphic features among Snapchat users of "Beauty-Retouching of Selfies" and its relationship with quality of life. *Media Asia, 49*(3), 196-212.

Ajiga, D. I., Ndubuisi, N. L., Asuzu, O. F., Owolabi, O. R., Tubokirifuruar, T. S., & Adeleye, R. A. (2024). AI-driven predictive analytics in retail: A review of emerging trends and customer engagement strategies. *International Journal of Management & Entrepreneurship Research, 6*(2), 307-321.

Alam, M., & Dover, J. S. (2001). On beauty: Evolution, psychosocial considerations, and surgical enhancement. *Archives of Dermatology, 137*(6), 795-807.

Alden, D. L., Steenkamp, J. B. E., & Batra, R. (1999). Brand positioning through advertising in Asia, North America, and Europe: The role of global consumer culture. *Journal of Marketing, 63*(1), 75-87.

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior, 114*, 106548.

Ando, K., Giorgianni, F. E., Danthinne, E. S., & Rodgers, R. F. (2021). Beauty ideals, social media, and body positivity: A qualitative investigation of influences on body image among young women in Japan. *Body Image, 38*, 358-369.

Androic, I. (2023). How virtual makeover technology helps brands sell real-world makeup. Retrieved February 24, 2025 from https://visagetechnologies.com/virtual-makeover-technology/

Ayar, D., Aksu, Ç., Polat, F., & Elkoca, A. (2025). The effects of popularity perceptions and social appearance anxiety on the desire of young people to have aesthetic procedures on social media. *Current Psychology*, 1-10.

Barari, M., Casper Ferm, L. E., Quach, S., Thaichon, P., & Ngo, L. (2024). The dark side of artificial intelligence in marketing: Meta-analytics review. *Marketing Intelligence & Planning, 42*(7), 1234-1256.

Bell, B. T., Taylor, C., Paddock, D., & Bates, A. (2022). Digital bodies: A controlled evaluation of a brief classroom-based intervention for reducing negative body image among adolescents in the digital age. *British Journal of Educational Psychology, 92*(1), 280-298.

Birkeland, R., Thompson, J. K., Herbozo, S., Roehrig, M., Cafri, G., & Van den Berg, P. (2005). Media exposure, mood, and body image dissatisfaction: An experimental test of person versus product priming. *Body Image, 2*(1), 53-61.

Boursier, V., Gioia, F., & Griffiths, M. D. (2020). Do selfie-expectancies and social appearance anxiety predict adolescents' problematic social media use? *Computers in Human Behavior, 110*, 106395.

Brown, J. D., Novick, N. J., Lord, K. A., & Richards, J. M. (1992). When Gulliver travels: Social context, psychological closeness, and self-appraisals. *Journal of Personality and Social Psychology, 62*(5), 717-729.

Caliskan, F., Idug, Y., Uvet, H., Gligor, N., & Kayaalp, A. (2024). Social comparison theory: A review and future directions. *Psychology & Marketing, 41*(11), 2823-2840.

Castillo-Hermosilla, M. P., Tayebi-Jazayeri, H., & Williams, V. N. (2023). Breaking the filtered lens: A feminist examination of beauty ideals in augmented reality filters. In *EAI International Conference on AI for People, Democratizing AI* (pp. 95-101). Cham: Springer Nature Switzerland.

Cleveland, M., & Laroche, M. (2007). Acculturation to the global consumer culture: Scale development and research paradigm. *Journal of Business Research, 60*(3), 249-259.

Dayan, S. H. (2011). What is beauty, and why do we care so much about it? *Archives of Facial Plastic Surgery, 13*(1), 66-67.

Dimitrov, D., & Kroumpouzos, G. (2023). Beauty perception: A historical and contemporary review. *Clinics in Dermatology, 41*(1), 33-40.

Dove. (2025). The Selfie Talk: Social media & self-esteem. Retrieved February 25, 2025 from https://www.dove.com/us/en/campaigns/purpose/theselfietalk.html

Ekinci, Y., & Riley, M. (2003). An investigation of self-concept: Actual and ideal self-congruence compared in the context of service evaluation. *Journal of Retailing and Consumer Services, 10*(4), 201-214.

Fardouly, J., Diedrichs, P. C., Vartanian, L. R., & Halliwell, E. (2015). Social comparisons on social media: The impact of Facebook on young women's body image concerns and mood. *Body Image, 13*, 38-45.

Festinger, L. (1954). A theory of social comparison processes. *Human Relations, 7*(2), 117-140.

Fioravanti, G., Bocci Benucci, S., Ceragioli, G., & Casale, S. (2022). How exposure to beauty ideals on social networking sites influences body image: A systematic review of experimental studies. *Adolescent Research Review, 7*, 419-458.

Frederick, D., Forbes, M., Jenkins, B., Reynolds, T., & Walters, T. (2015). Beauty standards. *The International Encyclopedia of Human Sexuality, 1*, 113-196.

Georgievskaya, A., Tlyachev, T., Danko, D., Chekanov, K., & Corstjens, H. (2025). How artificial intelligence adopts human biases: The case of cosmetic skincare industry. *AI and Ethics*, *5*, 105-115.

Gibbons, F. X., & Buunk, B. P. (1999). Individual differences in social comparison: Development of a scale of social comparison orientation. *Journal of Personality and Social Psychology, 76*(1), 129-142.

Grech, V. S., Kefala, V., & Rallis, E. (2024). Cosmetology in the era of artificial intelligence. *Cosmetics, 11*(4), 135.

Grewal, D., Benoit, S., Noble, S. M., Guha, A., Ahlbom, C. P., & Nordfält, J. (2023). Leveraging in-store technology and AI: Increasing customer and employee efficiency and enhancing their experiences. *Journal of Retailing*, *99*(4), 487-504.

Grogan, S. (2007). *Body image: Understanding body dissatisfaction in men, women and children* (2nd ed.). Hove: Routledge.

Harrison, K., & Cantor, J. (1997). The relationship between media consumption and eating disorders. *Journal of Communication, 47*(1), 40-67.

Hashemi, A., Shi, W., & Corriveau, J. P. (2024). AI-generated or AI touch-up? Identifying AI contribution in text data. *International Journal of Data Science and Analytics,* 1-12.

He, H., & Mukherjee, A. (2007). I am, ergo I shop: Does store image congruity explain shopping behaviour of Chinese consumers? *Journal of Marketing Management, 23*(5-6), 443-460.

Hefner, V., Woodward, K., Figge, L., Bevan, J. L., Santora, N., & Baloch, S. (2014). The influence of television and film viewing on midlife women's body image, disordered eating, and food choice. *Media Psychology, 17*(2), 185-207.

Higgins, E. T. (1987). Self-discrepancy: A theory relating self and affect. *Psychological Review, 94*(3), 319-340.

Hosany, S., & Martin, D. (2012). Self-image congruence in consumer behavior. *Journal of Business Research, 65*(5), 685-691.

Keillor, B. D., D'Amico, M., & Horton, V. (2001). Global consumer tendencies. *Psychology & Marketing, 18*(1), 1-19.

Kordzadeh, N., & Ghasemaghaei, M. (2022). Algorithmic bias: Review, synthesis, and future research directions. *European Journal of Information Systems, 31*(3), 388-409.

Kressmann, F., Sirgy, M. J., Herrmann, A., Huber, F., Huber, S., & Lee, D. J. (2006). Direct and indirect effects of self-image congruence on brand loyalty. *Journal of Business Research, 59*(9), 955-964.

Krishnamurthy, S., & Dou, W. (2008). Note from special issue editors: Advertising with user-generated content: A framework and research agenda. *Journal of Interactive Advertising, 8*(2), 1-4.

Krywuczky, F., & Kleijnen, M. (2024). Consumer decision-making in cosmetic surgery: An interdisciplinary review identifying key challenges and implications for marketing theory. *Psychology & Marketing, 41*(12), 3182-3201.

Kuipers, G. (2022). The expanding beauty regime: Or, why it has become so important to look good. *Critical Studies in Fashion & Beauty, 13*(2), 207-228.

Lashkari, S., & Sharma, S. (2023). Recommender systems and artificial intelligence in digital marketing. In *2022 OPJU International Technology Conference on Emerging Technologies for Sustainable Development (OTCON)* (pp. 1-8). IEEE.

Laughter, M. R., Anderson, J. B., Maymone, M. B., & Kroumpouzos, G. (2023). Psychology of aesthetics: Beauty, social media, and body dysmorphic disorder. *Clinics in Dermatology, 41*(1), 28-32.

Lavine, H., Sweeney, D., & Wagner, S. H. (1999). Depicting women as sex objects in television advertising: Effects on body dissatisfaction. *Personality and Social Psychology Bulletin, 25*(8), 1049-1058.

Levi Strauss & Co. (2023). LS&Co. Partners with Lalaland.ai. Retrieved February 25, 2025 from https://www.levistrauss.com/2023/03/22/lsco-partners-with-lalaland-ai/

Lewallen, J., & Behm-Morawitz, E. (2016). Pinterest or Thinterest?: Social comparison and body image on social media. *Social Media + Society, 2*(1), 1-9.

LG. (2021). Getting real with virtual influencer Reah Keem. Retrieved February 25, 2025 from https://www.lgnewsroom.com/2021/01/getting-real-with-virtual-influencer-reah-keem/

LG. (2022). Virtual artist Reah Keem ready to take the stage. Retrieved February 25, 2025 from https://www.lgnewsroom.com/2022/01/virtual-artist-reah-keem-ready-to-take-the-stage/

Mabry-Flynn, A., & Champlin, S. (2018). Leave a comment: Consumer responses to advertising featuring "real" women. In *Mediating Misogyny: Gender, Technology, and Harassment* (pp. 229-245). Springer.

MacCallum, F., & Widdows, H. (2018). Altered images: Understanding the influence of unrealistic images and beauty aspirations. *Health Care Analysis, 26*, 235-245.

Mandel, N., Rucker, D. D., Levav, J., & Galinsky, A. D. (2017). The compensatory consumer behavior model: How self-discrepancies drive consumer behavior. *Journal of Consumer Psychology, 27*(1), 133-146.

Nobile, V., Schiano, I., Germani, L., Cestone, E., Navarro, P., Jones, J., & Caturla, N. (2023). Skin anti-aging efficacy of a four-botanical blend dietary ingredient: A randomized, double blind, clinical study. *Cosmetics, 10*(1), 16.

O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown Publishing Group.

Onkvisit, S., & Shaw, J. (1987). Self-concept and image congruence: Some research and managerial implications. *Journal of Consumer Marketing, 4*(1), 13-23.

Pesonen, L. (2022). How Prada Candy and its digital muse is changing the fashion and beauty landscape. Retrieved February 25, 2025 from https://www.voguescandinavia.com/articles/how-prada-candy-and-its-digital-muse-is-changing-the-fashion-and-beauty-landscape

Prada. (2021). Rethink Reality: Prada Candy. Retrieved February 25, 2025 from https://www.prada.com/mc/en/pradasphere/fragrances/prada-candy/rethink-reality-prada-candy.html

Ramphul K. & Mejias S. G. (2018). Is "Snapchat Dysmorphia" a Real Issue?. *Cureus, 10*(3), e2263.

Rogers, C. R. (1959). A theory of therapy, personality, and interpersonal relationships: As developed in the client-centered framework. In *S. Koch (Ed.), Psychology: A study of a science* (Vol. 3, pp. 184-256). New York: McGraw-Hill.

Sethi, V., & Gujral, R. K. (2022). Survey of different recommendation systems to improve the marketing strategies on e-commerce. In *2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON)* (Vol. 1, pp. 119-125). IEEE.

Shokeen, J., & Rana, C. (2020). Social recommender systems: Techniques, domains, metrics, datasets and future scope. *Journal of Intelligent Information Systems, 54*(3), 633-667.

Singer, R., & Papadopoulos, T. (2024). There is no universal standard of beauty. *Aesthetic Plastic Surgery, 48*(24), 5273-5282.

Strahan, E. J., Wilson, A. E., Cressman, K. E., & Buote, V. M. (2006). Comparing to perfection: How cultural norms for appearance affect social comparisons and self-image. *Body Image, 3*(3), 211-227.

Struckman-Johnson, C., & Struckman-Johnson, D. (1994). Men's reactions to hypothetical female sexual advances: A beauty bias in response to sexual coercion. *Sex Roles, 31*, 387-405.

Tiggemann, M., & Polivy, J. (2010). Upward and downward: Social comparison processing of thin idealized media images. *Psychology of Women Quarterly, 34*(3), 356-364.

Vartanian, L. R. (2012). Self-discrepancy theory and body image. In *T. F. Cash (Ed.), Encyclopedia of body image and human appearance* (Vol. 2, pp. 711-717). Elsevier Academic Press.

We Are Social & Meltwater. (2025). *Digital 2025 Global Overview Report*. Retrieved February 24, 2025 from https://wearesocial.com/uk/blog/2025/02/digital-2025-the-essential-guide-to-the-global-state-of-digital/

Wills, T. A. (1981). Downward comparison principles in social psychology. *Psychological Bulletin, 90*(2), 245-271.

Wong, C. H., Wu, W. T., & Mendelson, B. (2021). Invited discussion on: What is beauty? *Aesthetic Plastic Surgery, 45*(5), 2177-2179.

Wood, J. V. (1996). What is social comparison and how should we study it? *Personality and Social Psychology Bulletin, 22*(5), 520-537.

Xie, Z. (2024). The influence of social media on perception of body image and beauty standards on young people. *Transactions on Social Science, Education and Humanities Research, 5*, 143-148.

Yan, Y., & Bissell, K. (2014). The globalization of beauty: How is ideal beauty influenced by globally published fashion and beauty magazines? *Journal of Intercultural Communication Research, 43*(3), 194-214.

Chapter 15

Artificial Intelligence Marketing (AIM): Digital Transformation and Consumer Behaviour

Ahmet Songur[1]

Abstract

Artificial intelligence (AI) is important in analyzing consumer behavior and creating marketing strategies based on this behavior. AI facilitates the analysis of large amounts of data, providing deep insights into consumer preferences. In this way, companies can increase customer satisfaction by offering personalized experiences that align with consumer expectations. Through machine learning and data analytics, consumer behavior can be better understood, increasing the effectiveness of marketing campaigns. AIM's ability to analyze data such as social media interactions, purchase history, and online behavior makes it possible to predict consumers' future buying tendencies. This enables marketers to target and quickly adapt to consumer behavior accurately. In addition, the personalization capabilities offered by AIM increase brand loyalty and strengthen purchase intent by providing consumers with personalized experiences. These benefits of AIM in understanding consumer behavior allow marketers to develop more effective and targeted strategies. The ability of technology to optimize marketing processes by responding to customer needs in real time allows brands to gain a competitive advantage. AIM has great potential to predict consumer behavior and create personalized marketing campaigns more accurately.

1. Introduction

The impact of artificial intelligence (AI) is becoming increasingly widespread, radically changing global marketing dynamics (Jain & Aggarwal, 2020). This technology, which transforms how businesses operate, holds significant potential for innovation in marketing. Identifying the most suitable AI solutions for marketing processes is a critical focus for practitioners. AI is expected to become an organization's key business

1 Doktor Öğretim Üyesi, Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi İşletme Bölümü, ahmetsongur@sdu.edu.tr, Orcid No: 0000-0002-9869-5394

https://doi.org/10.58830/ozgur.pub710.c3032

partner in the long term. AI applications have already become a core element of global marketing teams. In interviews with 100 senior marketers across various industries, it was found that 55 percent of companies are either using or actively researching AI-based marketing applications (Smartinsights, 2018). This finding underscores the transformational impact of AI on the marketing industry.

Artificial Intelligence Marketing (AIM) refers to the effective application of technology to enhance the customer experience. Artificial intelligence facilitates big data analysis, enabling personalized sales strategies and better alignment with customer expectations. Additionally, AIM has the potential to improve the performance and return on investment (ROI) of marketing campaigns by providing rapid and in-depth customer insights (Jain & Aggarwal, 2020).

In the marketing landscape, big data analytics and artificial intelligence applications are becoming increasingly crucial. By leveraging machine learning technologies, marketers analyze the relationships between data points to gain deep insights into customer behavior and enhance operational efficiency. These systems can detect emotions by analyzing speech, visualize social media trends, and make various predictions through data processing (Thiraviyam, 2018).

AI holds significant potential in the field of marketing, fundamentally transforming the interaction between brands and consumers. The application of AI varies based on the type of business and the characteristics of the website. The data generated by AI allows for the rapid and effective identification of content and channel preferences within the target audience, enabling marketers to meet customer needs in real time. Furthermore, the personalization capabilities offered by AI provide a sustainable competitive advantage by analyzing the performance of competing businesses while enhancing consumers' purchasing tendencies (Haleem et al., 2022).

New technologies offer a competitive advantage to businesses by making their product and service offerings more accessible to customers (Rouhani et al., 2016). A customer-centered approach that focuses on addressing customer needs on a global scale is essential for organizational growth (Vetterli et al., 2016). AI plays a significant role, particularly in digital marketing. Through tools such as chatbots, intelligent email marketing, interactive web design, and other digital marketing technologies, AI helps guide users in alignment with business objectives, providing a more personalized experience. These technologies optimize customer interactions, making marketing strategies more effective for businesses.

With the advancement of AI, artificial intelligence applications in marketing have become increasingly important for enhancing customer satisfaction, expanding market share, and boosting profitability. In this context, key questions arise regarding how AI technologies can be most effectively integrated into marketing strategies and what future research directions will emerge. Artificial intelligence offers marketers significant opportunities by providing advantages such as the ability to analyze customer behavior, deliver personalized experiences, and accelerate decision-making processes. Future research will focus on exploring more in-depth applications of AI, examining its impact on marketing strategies, and investigating ways to integrate these technologies more sustainably and ethically (Wisetsri et al., 2021).

2. Artificial Intelligence (AI) Concept

In artificial intelligence (AI), the term 'artificial' refers to the capacity of machines to function independently of human intervention, while the concept of 'intelligence' is more nuanced and complex (Wirth, 2018). Alan Turing addressed this issue in his 1950 paper, *Computing Machinery and Intelligence*, which preceded John McCarthy's Dartmouth Artificial Intelligence Research Project in 1956. In his discussion of the question "Can machines think?", Turing emphasized the need to first define the concepts of 'machine' and 'thinking' (Turing, 1950). The Turing test is designed to assess the intelligence of computers and determine whether a machine can achieve human-level performance across all cognitive tasks (Thiraviyam, 2018). In 1959, Cahit Arf addressed the issue in his Public Conference Declaration at Atatürk University in Erzurum under the title 'Can a machine think and how can it think? (Arf, 1959).

Artificial intelligence, from an idealized perspective, can be seen as an artificial operating system that demonstrates the higher cognitive functions or autonomous behaviors typically associated with human intelligence. This system should be capable of perceiving, learning, linking multiple concepts, thinking, reasoning, problem-solving, communicating, and making decisions. Additionally, such an AI system should be able to generate responses based on its reasoning (agentive artificial intelligence) and physically express these reactions (Wikipedia, 2025).

Wirth (2018) defines AI in three distinct categories: narrow AI, hybrid AI, and strong AI. Narrow AI, also known as weak AI, refers to systems optimized for specific tasks, with limited flexibility and an inability to adapt to different domains. Despite this limitation, the development of narrow

AI systems is highly complex. While these systems lack the broad cognitive capabilities of human intelligence, they can excel in their areas of expertise and even surpass humans in some cases. Notable examples include AlphaGo and DeepBlue. The majority of AI systems in use today fall under the narrow AI category, such as Siri, Google Assistant, and Alexa. Narrow AI is widely applied across industries like healthcare, defense, and marketing. The terms strong AI, full AI, and general artificial intelligence are used interchangeably to describe systems that possess the same level of power and flexibility as human intelligence. Unlike narrow AI, strong AI is not designed for specific tasks but aims to replicate human cognitive capabilities. However, strong AI has not yet been realized (Greenwald, 2011). The development of narrow AI has highlighted the need for more precise terminology. Emerging solutions that integrate multiple narrow AI systems to address a broader range of tasks are referred to as hybrid AI. This field is rapidly expanding, though these systems still do not qualify as strong AI (Martínez de Pisón et al., 2017).

In today's rapidly evolving digital landscape, data-driven strategies are becoming increasingly vital in marketing. In this context, technologies such as Big Data and Machine Learning are transforming marketing practices. Big Data refers to the process of collecting extensive data on customers' buying behaviors and trends. It also involves the ability of marketers to effectively combine and analyze large data sets. This data is leveraged in marketing strategies to ensure that the right message reaches the right person at the right time and through the appropriate channel. Machine Learning, on the other hand, enables the creation and application of models based on identified patterns. This technology provides the opportunity to uncover trends, analyze insights, and predict behaviors by extracting valuable information from large data sets. As a result, marketers can optimize their strategic decisions by better assessing the likelihood of certain actions being repeated and understanding the key factors influencing these processes (Jain & Aggarwal, 2020).

In the realm of artificial intelligence and machine learning, few topics are as intriguing as generative models. These models stand out for their ability to generate new data that closely resembles real-world examples. Generative models tackle one of the most complex challenges in AI: creating new data that is indistinguishable from authentic data. They can generate realistic images, music, or text without human intervention. Among these models, Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) are particularly notable architectures. Generative Adversarial Networks (GANs), developed by Ian Goodfellow and his team in 2014, consist of two opposing neural networks: the Generator and the

Discriminator (Goodfellow, 2014). The Generator creates realistic data samples starting from random noise, while the Discriminator analyzes the generated data and attempts to distinguish between real and fake samples. These two networks continuously challenge each other— as the Generator produces more convincing fake data, the Discriminator becomes increasingly adept at detecting it. This adversarial process enables the Generator to create samples so realistic that they are almost indistinguishable from real data (Alqahtani et al., 2021). Variational Autoencoders (VAEs) enhance the dimensionality reduction and feature learning capabilities of traditional Autoencoders by introducing a probabilistic framework for generative modeling. In this model, the Encoder maps the input data into a low-dimensional latent space, creating a probabilistic representation, while the Decoder reconstructs the original data by sampling from this latent space (Wei et al., 2020). The key feature of VAEs is that they treat the latent space as a probability distribution, allowing for more flexible and controlled data generation. This probabilistic approach provides a statistical structure that enables the model to generate new data samples. Generative models have found widespread applications across various fields, including art production, anomaly detection, drug discovery, super-resolution image processing, and data transfer (Sruthy, 2023).

3. AIM and Consumer Behavior

AI is a technology that enables businesses to monitor real-time data, allowing them to quickly analyze and respond to customer needs (Wirth, 2018). Marketers can use AI to assess consumer behavior, identify patterns, predict future outcomes, and adjust advertising strategies accordingly. AI offers significant advantages for marketers, particularly in forecasting consumer behavior and enhancing customer satisfaction. As consumer preferences evolve, brands are increasingly investing in AI-powered solutions to maintain a competitive edge. AI tools are being effectively applied in areas such as web metrics analysis, optimization of reach, and conversion strategies. AI branches, including machine learning, natural language processing, expert systems, robotics, and data analytics, help marketers classify customer needs, personalize demand, and improve sales forecasts. AI-powered 'intelligent' systems are designed to boost customer loyalty and sales performance while reducing uncertainties in decision-making processes (Gkikas & Theodoridis, 2022).

Traditionally, forecasting consumer behavior relied on statistical techniques and rule-based systems. While these methods can be useful to some extent, contemporary consumer markets are increasingly analyzed using generative artificial intelligence (AI) methods, which have significantly enhanced the accuracy and depth of consumer behavior predictions. By utilizing large datasets and complex machine learning algorithms, these models can uncover hidden trends and relationships that traditional methods often overlook. For example, Generative Adversarial Networks (GANs) create realistic customer profiles based on existing data, enabling marketers to simulate how new products or services will be perceived by different populations (Prosvetov, 2019). Similarly, Variational Autoencoders (VAEs) analyze the latent variables behind consumer preferences, providing a more comprehensive understanding of individual choices and how these decisions are influenced by external factors (Higgins et al., 2017).

The increasing availability of consumer data and artificial intelligence (AI) systems developed for large-scale processing of this data has accelerated data-driven decision-making processes in marketing. Generative AI models provide an effective tool to improve traditional consumer behavior models by offering more accurate and complex insights. Transformative models in particular have shown great success in recommender systems. For example, they are notable for their ability to accurately predict future behavior and preferences by analyzing customer contact data (Yenduri et al., 2024; Gupta et al., 2024; Yoon & Jang, 2023).

The use of generative artificial intelligence (AI) in marketing has created new opportunities and influenced consumer behavior. These technologies enable companies to create customized marketing plans, evaluate big customer data more effectively, and gain new insights. Personalized marketing, in particular, is an important area where generative AI is having an impact. While traditional methods rely on rule-based algorithms that group users into groups, generative AI can create unique customer profiles and detect small trends by analyzing behavioral data. By modeling how consumers react to marketing stimuli, GANs enable companies to deliver more accurately personalized messages. This level of personalization can increase consumer engagement and loyalty (Gavilanes et al., 2018; Harmeling et al., 2017). Furthermore, transducers can be used to predict consumer behavior. For example, in e-commerce, a model can provide timely and relevant product recommendations by predicting a consumer's future purchases. Generative AI models are also effective in sentiment analysis and recognition and play an important role in understanding factors such as customer satisfaction and dissatisfaction. This information can be used to improve customer service and build stronger consumer relationships (Higgins, et. al., 2017).

Madanchian (2024) examines the impact of AI models on consumer behavior prediction, marketing, and customer engagement. By systematically analyzing 31 studies across areas such as e-commerce, energy data modeling, and public health, he identifies the contributions of these models to personalized marketing, inventory management, and customer retention. The study highlights the ability of transformative models to process complex data, as well as the advantages of certain AI models (e.g., GAN and VAE) in predicting customer behavior. Additionally, challenges related to data privacy, computing resources, and the application of these models in real-world scenarios are discussed.

4. Use of Artificial Intelligence in Marketing

The primary applications of AI in marketing encompass key marketing mix elements, including strategy and planning, product development, pricing, distribution, and promotion. The use of AI-based systems in these areas is strategically significant (Han et al., 2021).

Figure 1. Several Segments for AI Applications in the Marketing Domain

Source: Haleem et al., 2022: p. 121.

4.1. Strategy and Planning

AI can assist marketers in determining the strategic direction of a company (Huang & Rust, 2017). Additionally, AI supports marketers in segmentation, targeting, and positioning, enabling them to develop effective marketing strategies and plan their activities. AI applications are particularly useful in identifying profitable customer segments across various industries, especially in retail. By combining data optimization techniques, machine learning, and causal forests, marketers can refine customer targeting (Chen et al., 2020; Dekimpe, 2020; Pitt et al., 2020). These capabilities help marketers create more effective and efficient planning strategies.

Huang and Rust (2021) developed a three-stage framework for strategic marketing planning that incorporates the advantages of artificial intelligence (AI). This framework describes different types of AI used to optimize marketing processes: Mechanical AI is used to automate repetitive marketing functions and activities; Thinking AI is used to process data to make decisions; and Feeling AI is used to analyze interactions and human emotions. This three-stage framework illustrates how AI can be used for marketing research, strategy (segmentation, targeting, positioning), and actions. In the marketing research phase, mechanical AI can be used to collect data, thinking AI can be used to analyze the market, and feeling AI can be used to gain customer insight. In the marketing strategy phase, mechanical AI can be used for segmentation, thinking AI for targeting, and feeling AI for positioning. At the marketing action stage, mechanical AI can be used for standardization, thinking AI for personalization, and feeling AI for relationalisation. This framework is applied to various areas of marketing and according to the marketing 4P/4C framework to illustrate the strategic use of AI (Shree, 2024)

The impact of AI on the marketing mix lies at the core of digital transformation, revolutionizing marketing strategies. This influence allows brands to create more targeted, effective, and personalized strategies by offering innovative, data-driven solutions in product, price, distribution, and promotion. The table below highlights the impact and application areas of artificial intelligence on the marketing mix.

Table 1: The Impact of Artificial Intelligence on Key Marketing Mix Strategies

Product	Price	Promotion	Place
• Development of new product • Personalization of the product • Automatic suggestions to the buyers • Creating added value for the customer	• Creating prices in accordance with the buyer's power	• Creating a unique customer experience • Personalization of comunication • Creating new value and benefits for the customers • Decreasing disappointing effect	• New distribution channels • Continuous customer support • Automatization of the sales

Source: Buntak et al., 2021: p. 410.

4.2. Product Management

AI can tailor offers to meet customers' needs. An AI-based marketing analytics tool can enhance customer satisfaction by evaluating how well product designs align with customer preferences (Dekimpe, 2020). During product searches, preference weights assigned to product attributes help marketers better understand the product recommendation system and adjust marketing strategies for effective product management. Topic modeling improves the system's ability to innovate and design services, while deep learning personalizes interest recommendations, helping to discover new places (Antons & Breidbach, 2018; Dzyabura & Huser, 2019; Guo et al., 2018).

4.3. Price Management

Pricing is a computationally intensive process that involves considering multiple factors to determine the final price. The complexity of this process is further heightened by real-time price adjustments driven by fluctuating demand. In such a dynamic environment, a multi-armed bandit algorithm powered by artificial intelligence can adjust prices in real-time (Misra et al., 2019). For environments where prices change frequently, such as e-commerce platforms, Bayesian inference within machine learning algorithms can quickly align price points with competitor prices (Bauer & Jannach, 2018). The most effective pricing algorithms integrate customer preferences, competitor strategies, and supply networks to optimize dynamic pricing (Dekimpe, 2020). On the application side, AI-powered tools such as big data analytics are used for price adjustments and forecasting.

4.4. Place Management

Product access and availability are critical components of the marketing mix for enhancing customer satisfaction. Product distribution is a largely mechanized and iterative process that depends on network relationships, logistics, inventory management, storage, and transportation. AI is an ideal solution for location management, with technologies such as cobots for packaging, drones for delivery, and IoT systems for order tracking and fulfillment (Huang & Rust, 2018). Both suppliers and customers benefit from the standardization and automation of the distribution process. In addition to its advantages in distribution management, AI also presents opportunities for customer engagement in service contexts. Service robots, programmed with emotional AI, can enhance customer interactions (Wirtz et al., 2018). While tangible robots engage with customers, human elements remain essential in complementing the service environment to ensure customer satisfaction. AI-driven service process automation further provides opportunities for performance and productivity improvements (Gür, 2022).

4.5. Promotion Management

Product access and availability are critical components of the marketing mix for enhancing customer satisfaction. Product distribution is a largely mechanized and iterative process that depends on network relationships, logistics, inventory management, warehousing, and transportation. AI provides an ideal solution for location management, utilizing technologies such as cobots for packaging, drones for delivery, and IoT systems for order tracking and fulfillment (Huang & Rust, 2018). Both suppliers and customers benefit from the standardization and automation of the distribution process. Beyond its advantages in distribution management, AI also presents opportunities for customer engagement in service contexts. Service robots programmed with emotional AI can significantly enhance customer interactions (Wirtz et al., 2018). While physical robots engage with customers, human elements remain crucial in complementing the service environment to ensure customer satisfaction. AI-driven automation of service processes also offers additional opportunities to improve performance and productivity (Gür, 2022).

Table 2 outlines the key applications of AI in marketing and illustrates the new opportunities it presents for companies to achieve a sustainable competitive advantage in an increasingly digital and data-driven world.

Table 2. Major Implementations of AI in Marketing

Applications	Description	References
Digital Marketing	• Analyzing consumer behavior, actions, and key indicators • Accurate targeting and optimal timing • Data processing across social media, email, and websites • Marketing automation: data flow, interactions, and business outcomes • Data collection, insights generation, predictions, and automated decision-making	(Yang et al., 2022; Paschen et al., 2021; Shah & Shay, 2020; Syam & Sharma, 2018;)
Reduction of human mistakes	• Reduces human error in marketing processes • Content development and optimization, such as email format personalization • Minimizes the risk of human error in decision-making • Addresses data security concerns and safeguards against breaches • Enhances employee competence in protecting customer and company data • Adapts to tackle cybersecurity challenges • Optimizes marketing strategies, reducing the need for excessive resources	(Ekramifard, A., Amintoosi, H., Seno, A.H., Dehghantanha, A., Parizi, 2020; Kitsios, F.; Kamariotou, 2021; Tan et al., 2016)
Connect business process	• Connects end-to-end business processes for a seamless experience. • Marketers using AI achieve exceptional performance. • Enables the creation of customized, human-centered marketing strategies. • Transforms customers into passionate brand advocates. • AI enhances interaction designs, making them more engaging. • Offers organizations the opportunity to elevate marketing to a superior experience.	(Akansha Mer, 2022; Grewal et al., 2020; Sadriwala, M. F. & Sadriwala, 2022; Yablonsky, 2019)
Analyse massive amounts of market data	• Analyzes vast amounts of market data to predict user behavior. • Understands billions of search queries to assess purchase intent. • Identifies gaps and facilitates appropriate actions. • AI and machine learning extend beyond basic tools. • Fundamentally transforms business operations. • Increases business efficiency nearly threefold.	(De Bruyn et al., 2020; He et al., 2020; Moudud-Ul-Huq, 2014; V. Rutskiy, R. Mousavi, N. Chudopal, Y.E. Amrani, V. Everstova, 2021)

Applications	Description	References
Deliver valuable information	• Analyzes new data to provide customers with more relevant information. • Acts as a tool to drive marketing campaigns toward higher goals. • Combines advanced technology and human intelligence for hyper-personalized, engaging interactions. • Delivers instant personalized advertising. • Continuously collects data to guide future ad content changes. • Enables sellers to focus on results using personal and behavioral data. • Provides deeper insights into customer goals, aspirations, and buying patterns.	(Brooks, 2022; Makarius et al., 2020; Purwanto P., Kuswandi K., 2020)
Enable convenient customer support	• Provides intelligent, simple, and convenient customer support at every stage for an optimal experience. • Essential for ensuring a seamless and efficient customer experience. • Automates repetitive marketing tasks to enhance marketing automation. • Captures real-time customer data and scales its application. • Simplifies sorting, organizing, and prioritizing data. • AI-powered marketing automation tools are transforming marketing strategies. • Next-generation platforms strengthen strategies by addressing evolving needs like hyper-personalized offers.	(Buntak et al., 2021; Sirajuddin & P, 2020; Jatobá et al., 2019; Fish & Ruby, 2009;)
Better marketing automation tool	• Enables marketers to identify qualified leads, refine nurturing tactics, and create relevant content by integrating with marketing automation tools. • Dynamic content emails, particularly one-to-one messages, effectively reinforce a brand's message by delivering contextual emails that capture subscribers' attention. • Dynamic content strategies ensure email relevance by considering factors such as geographic location, psychographics, behavioral data, and insights.	(Alyoshina, 2020; K. Jarek, 2019; Tanase & Cosmin, 2018)

Applications	Description	References
Ease workload	• Provides actionable insights from complex data within a short time frame. • Has the potential to significantly impact marketing activities through predictive analytics. • AI-driven predictive analytics unlocks substantial value from existing data. • Predictive lead scoring offers an innovative method for ranking and evaluating leads.	(Huang & Rust, 2021; Mohd Javaid, Abid Haleem, Ravi Pratap Singh, 2022; Vlačić et al., 2021; Wirth, 2018)
Speeds up data processing	• Enhances data processing speed, accuracy, and security, allowing teams to focus on strategic objectives while creating effective campaigns. • Collects and tracks real-time tactical data, enabling immediate decision-making. • Facilitates smarter, more objective decision-making through data-driven reports. • AI automates repetitive and time-consuming tasks, completing them efficiently and error-free. • Substantially reduces recruitment costs through automation and AI-driven efficiencies.	(Kumar, Rajan, Venkatesan, & Lecinski, 2019; Davenport, Guha, Grewal, & Bressgott, 2020; Raiter, 2021)
Make customer centered choices	• AI enhances consumer understanding, enabling more customer-centric decision-making. • Provides external market intelligence by analyzing social media and web content. • Enables marketers to quickly build detailed consumer profiles using big data. • Consumer profiles encompass interactions, campaign responses, habits, and other relevant factors.	(Rekha, Abdulla, & Asharaf, 2016; Paschen, Kietzmann, & Kietzmann, 2019: Feng, Park, Pitt, Kietzmann, & Northey, 2021)
Examine data about customer	• .Machine learning identifies the optimal times, frequency, engaging content, and effective email subject lines for customers. • Complex algorithms personalize the web experience for individual users. • Data is analyzed to provide more relevant offers tailored to each user. • Predictive models estimate the likelihood of leads converting into customers. • These models can also determine the price needed to convert leads or identify customers likely to make repeat purchases.	(Mustak, Salminen, Plé, & Wirtz, 2021; Olson & Levy, 2018; Vishnoi, Bagga, Sharma, & Wani, 2018)

Applications	Description	References
Improve stock control	• AI enhances inventory control during peak demand, preventing over-buying and maximizing revenue. • Every business has unique dynamic pricing and demand forecasting requirements. • Tailoring solutions based on specific products and customer types is often the best approach to meet business goals.	(Aladayleh, 2020; Wierenga, 2010; Nalini, Radhakrishnan, Yogi, Santhiya, & Harivardhini, 2021; Rodgers & Nguyen, 2022)
Customise shopping processes	• AI can create simulation models, personalize shopping experiences, and offer product recommendations. • Companies, like Amazon, utilize AI to engage customers by suggesting products based on past purchases and searches. • Intelligent technologies are evolving rapidly and can outperform humans in certain areas. • AI is surpassing humans in recognizing marketing trends due to its vast data analysis capabilities. • These systems analyze data to predict consumer buying patterns and enhance the user experience.	(Pedersen & Duin, 2022; Khrais, 2020; Kumar, 2020)
Digital advertising	• AI helps achieve success in digital advertising by targeting experts on platforms like Facebook, Google, and Instagram. • Ads are tailored by analyzing user data such as gender, age, interests, etc. • Marketers can leverage AI to analyze micro-trends and forecast future trends. • This enables more informed and strategic decision-making. • Companies can maximize return on investment by minimizing digital advertising waste. • AI, combined with IoT and connected devices, is shaping the future of digital marketing.	(Martínez-López & Casillas, 2013; Boz & Kose, 2018; Kietzmann & Pitt, 2020; Alawaad, 2021)
Better customer experience	• AI is used to enhance operational efficiency and improve the consumer experience. • Marketers can leverage these platforms to gain a deeper, more comprehensive understanding of their target audience. • The collected data helps boost conversions while reducing the effort required from marketing teams.	(Rust & Huang, 2014; Güngör, 2020; Dwivedi et al., 2021)

Applications	Description	References
Assisting marketers	• AI enables more effective customer interactions. • AI marketing components analyze large customer datasets and provide tech-driven solutions for future actions. • With the rise of digital media, big data has expanded, allowing marketers to analyze campaigns in greater depth and transfer data across multiple channels. • Effective AI solutions offer marketers a centralized platform to manage large data volumes efficiently.	(Bader & Kaiser, 2019; Enholm, Papagiannidis, Mikalef, & Krogstie, 2021; Loureiro, Guerreiro, & Tussyadiah, 2021)
Increased customer satisfaction and revenue	• AI reduces risk, boosts speed, enhances customer satisfaction, and increases marketing revenue. • It enables fast decisions on media channel spend allocation, maximizes campaign value, and fosters interaction. • AI improves customer experience by delivering personalized messages at optimal times. • It identifies high-risk customers and suggests strategies to re-engage them. • It analyzes strategy effectiveness and ensures appropriate resource allocation.	(Popova, 2017; Deggans, Krulicky, (Kovacova, Valaskova, & Poliak, 2019; Tchelidze, 2019; Sajid, Haleem, Bahl, Javaid, Goyal, & Mittal, 2021)
Develop-ment of a predictive model	• AI assists with data collection, predictive modeling, and testing. • It sends personalized emails and enhances customer experience. • Identifies customer groups at risk of abandonment or switching to competitors. • Analyzes multi-channel activity to predict abandonment and improve engagement. • Keeps users engaged with relevant offers, alerts, and emails. • Combining AI-powered abandonment prediction with personalized content boosts engagement and revenue.	(Yawalkar, 2019; Sahai & Goel, 2021; Vrontis, Christofi, Pereira, Tarba, Makrides, & Trichina, 2022)
Learning about customer preferences	• AI helps marketing teams understand customer preferences and demographics. • This allows for personalized experiences tailored to each customer. • Data can create detailed customer profiles, such as how they respond to headlines or visuals. • These insights inform and improve future marketing messages.	(Siau & Wang, 2018; Chatterjee, Chaudhuri, Vrontis, Thrassou, & Ghosh, 2021; Spreitzenbarth, Stuckenschmidt, & Bode, 2021)

Applications	Description	References
Make better decisions	• AI enhances insights by analyzing both quantitative and qualitative data. • In Google Ads, AI helps focus on high-level decisions, like campaign planning. • It enables more targeted campaigns and better ROI by processing large data sets. • Agencies can leverage AI to analyze data, predict trends, and improve brand quality. • AI fosters the creation of innovative, targeted ads. • Agencies can use AI to increase revenue while reducing costs.	(Prabowo, Murdiono, Hidayat, Rahayu, & Sutrisno, 2019; Farrokhi, Shirazi, Hajli, & Tajvidi, 2020; Boddu, Santoki, Khurana, Koli, Rai, & Agrawal, 2022)
Target audience	• Companies must understand their customers' needs and expectations. • AI marketing helps deliver more personalized experiences. • It enhances the efficiency of conversion management solutions. • Marketers can address strategic challenges through the analysis of sophisticated communications. • As consumer expectations evolve, there's increasing demand for customized experiences.	(Daqar & Smoudy, 2019; Lies, 2019; Dubey, Bryde, Blome, Roubaud, & Giannakis, 2021; Giroux, Kim, Lee, & Park, 2022)
Deliver the right message in time	• Helps marketers gain deeper insights into their customers. • Building a comprehensive profile involves collecting data from all customer interactions. • Enables the creation of personalized content and improved campaigns. • Facilitates the creation of innovative digital advertising using online data.	(Pangkey, Furkan, & Herman, 2019; Li, Cao, Ye, & Yue, 2021; Zhao & Cai; 2021)
Assist businesses	• Helps businesses understand their customers and deliver personalized experiences. • Companies can target using purchase history and social media data. • Plays a key role in optimizing ad performance. • Social media platforms use AI to automate ads and analyze performance. • Improves campaign performance by optimizing targeting and ad spending.	(Haleem & Javaid, 2019; Singh, Flaherty, Sohi, Deeter-Schmelz, Habel, Le Meunier-FitzHugh, & Onyemah, 2019; Kaiyp & Alimanova, 2020; Ahmed & Ganapathy, 2021)

Source: Haleem et al., 2022: pp. 124-127.

5. Examples of Artificial Intelligence in Marketing

A survey found that 46% of respondents reported that their interaction with technology increased their trust in a brand and fostered a positive perception. Alibaba has integrated artificial intelligence and smart clothing labels into fashion retail by launching a store called 'FashionAI' in Hong Kong. This system uses product-recognition tags and smart mirrors that suggest complementary items, complete with garment descriptions. Alibaba's next goal is to allow customers to create a virtual wardrobe from clothes they've tried on or touched while visiting the store. This innovative technology has been developed in response to evolving consumer expectations (Norris, 2024).

A survey revealed that 46% of respondents stated their interaction with technology enhanced their trust in a brand and cultivated a positive perception. Alibaba has integrated artificial intelligence and smart clothing labels into fashion retail by launching a store named 'FashionAI' in Hong Kong. This system employs product recognition tags and smart mirrors that suggest complementary items along with garment descriptions. Alibaba's next goal is to allow customers to build a virtual wardrobe from clothes they've tried on or interacted with during their visit to the store. This innovative technology was developed in response to the evolving expectations of consumers (Norris, 2024).

Netflix offers personalized content recommendations through artificial intelligence applications. The platform analyzes users' viewing history, preferences, and reactions to various series, documentaries, and films. This AI-driven system processes billions of data transactions to recommend content, forming a significant portion of the content users discover (*Pegasusone*, 2025).

Netflix offers personalized content recommendations through AI applications. The platform analyzes users' viewing history, preferences, and reactions to various series, documentaries, and films. The AI-powered system processes billions of data transactions to recommend content, which constitutes a significant portion of the content discovered by users (*Pegasusone,* 2025).

Starbucks has developed an AI strategy based on predictive analytics, utilizing loyalty cards and mobile applications to collect and analyze consumer data. As part of this strategy, announced in 2016, personalized marketing messages and recommendations were sent to customers. Additionally, voice-command ordering was integrated into the mobile app to enhance the user experience. These AI applications contributed to the company's 11% annual revenue growth in 2018, compared to the previous year (*Macrotrends*, 2025).

Unilever has leveraged artificial intelligence to align insights from reference pools, such as popular media content and music, with food consumption trends. Through these analyses, a connection was discovered between breakfast and ice cream consumption. Seizing this trend as an opportunity, Unilever developed cereal-flavored ice cream and the concept of "Breakfast for Desserts," which has since become an industry standard (*Spiceworks*, 2019).

6. Conclusion

Innovations such as personalization, speech and image recognition, chatbots, churn prediction, dynamic pricing, and customer insights powered by artificial intelligence marketing are increasingly making traditional marketing techniques less effective. While AIM (Artificial Intelligence Marketing) technologies are rapidly reshaping marketing strategies and business models, some traditional areas of market research may be replaced by machines. This shift is leading to the elimination of jobs requiring fewer technical skills and the emergence of new business areas demanding high potential and advanced expertise. Today, AIM is not only transforming marketing strategies but also influencing customer behavior. This change marks a significant evolution in the marketing world, and it will be fascinating to see how the field continues to evolve in the future.

Data analytics is one of the most significant benefits of AI in marketing. This technology analyzes large volumes of data and provides marketers with real and actionable insights. Artificial intelligence (AI) is emerging as a crucial tool for enhancing the customer experience. For instance, a Harley Davidson dealership in New York tripled its revenue and generated 2930% more leads by using predictive analytics on an AI-based marketing platform, highlighting the potential of AI in marketing (Anoop MR, 2021).

Several studies have highlighted the effectiveness of AI in enhancing customer experiences. For example, Nguyen and Sidorova (2018) demonstrated that AI-powered chatbots improve customer interactions (Nguyen & Sidorova, 2018). Additionally, Gacanin and Wagner (2019) discussed the potential of AI and machine learning to generate significant business value, while addressing the challenges of implementing autonomous customer experience management (Gacanin & Wagner, 2019). Chatterjee et al. (2019) emphasized how AI analyzes customer habits, buying behavior, and preferences to deliver personalized experiences (Chatterjee et al., 2019). Seranmadevi and Kumar (2019) outlined AI's key role in customer relationship management and user interface applications (Seranmadevi & Kumar, 2019). Sujata et al. (2019) noted the transformation of traditional stores into "smart stores" with AI applications, leading to supply chain efficiencies and enhanced customer experience (Sujata et al., 2019). Finally, Sha and Rajeswari (2019) pointed out that AI-supported technologies in the e-commerce sector have strengthened consumer-brand relationships and product interactions by monitoring consumers' five senses (Sha & Rajeswari, 2019). Maxwell et al. (2011) found that AI enhances marketing decision-making by improving the efficiency of data processing (Maxwell et al., 2011). Wisetsri et al. (2021) conducted a systematic review of the literature on AI in marketing research. Their bibliometric analysis, which covered more than 500 articles published between 1995 and 2020, highlighted the key contributors, sources, and scientific actors in the field, and explored the impact of AI on marketing. In their study, Davenport et al. (2020) proposed a framework for understanding AI's influence on marketing strategies and customer behavior. They noted that while the short- and medium-term impact of AI may be more limited, its effectiveness will increase when it augments human managers rather than replacing them. Soni et al. (2020) explored the impact of AI on business, offering a comprehensive perspective from innovation and research to market adoption and future business model changes. They identified two key drivers behind AI's emergence as the primary technology for over-automation and discussed the concept of the "AI divide," or the "dark side of AI." Shahid and Li (2019) conducted a qualitative study with marketing professionals from various companies to emphasize the benefits of integrating AI into marketing strategies, while also highlighting technical compliance as one of the biggest challenges in this process. Overgoor et al. (2019) provided a detailed explanation of how an industry-standard data mining framework can be applied to develop AI solutions for marketing problems, supported by a compelling case study on automated image scoring for digital marketing. Quasim and Chattopadhyay (2015) explored various types of forecasting and artificial intelligence (AI) techniques used in business forecasting, providing insights into promising AI approaches for this field. Kim (2014) conducted in-depth interviews with 20 marketing executives to examine the topology and characteristics of big data marketing strategies, emphasizing the business implications of big data analytics. Amado et al. (2018) evaluated the application of big data in marketing, noting the growing interest in this area and urging companies to enhance their efforts in developing big data capabilities. Özçelik and

Varnalı (2019) examined the psychological aspects and consumer behaviors related to the effectiveness of customized online advertising using behavioral targeting. They concluded that consumers' promotional focus significantly influences their perceptions of the informativeness and entertainment value of tailored ads. Simon (2019) discussed the key trends in artificial intelligence, highlighting the uncertainty surrounding demand from both business and consumer sides, along with the legal, ethical, and socio-economic challenges that may impede the widespread deployment of AI technologies.

Modern technology exists as a holistic system, with all its components interconnected. It is impossible to embrace only the positive aspects of technology while avoiding its negative consequences. As a powerful and influential force, technology inherently presents trade-offs, often leading to the gradual erosion of individual freedoms. In many instances, society is compelled to adapt to these changes by integrating new technological tools (Kaczynski, 2013).

AI data must be protected and assessed within its ethical context. As advancements in artificial intelligence (AI) significantly transform marketing strategies, the question of how these changes will fit within personal data protection frameworks becomes increasingly critical. These regulations are designed to strengthen data protection and give individuals greater control over their personal information, which directly impacts AI-driven strategies like targeted advertising, customer analytics, and personalized marketing. AI's capacity for large-scale data processing and automated decision-making is an area that requires careful reassessment in the context of personal data protection. Regulatory principles, such as data minimization, explicit consent, and accountability for algorithmic decisions, require marketers to make their AI-driven solutions more transparent and accountable. In this context, ethical principles such as transparency, fairness, non-maleficence, responsibility, and privacy will play a key role in shaping the adoption and implementation of AI in marketing. For instance, fundamental ethical requirements for AI usage include ensuring that algorithms are free from bias and that consumer data is used responsibly. The level of ethical practice in AI will depend on factors such as an individual's awareness of data rights, the ethical policies of companies, and the regulatory oversight mechanisms in place. When these ethical principles are upheld, AI can evolve into a trustworthy and sustainable marketing tool that benefits consumers, businesses, and other stakeholders.

References

Ahmed, A. A. A., & Ganapathy, A. (2021). Creation of automated content with embedded artificial intelligence: A study on learning management system for educational entrepreneurship. *Academy of Entrepreneurship Journal, 27*(3), 1–10.

Alqahtani, H., Kavakli-Thorne, M., & Kumar, G. (2021). Applications of generative adversarial networks (GANs): An updated review. *Archives of Computational Methods in Engineering, 28*, 525–552. https://doi.org/10.1007/s11831-019-09388-y

Arf, C. (1959). *Makine düşünebilir mi ve nasıl düşünebilir?* Atatürk Üniversitesi – Üniversite Çalışmalarını Muhite Yayma ve Halk Eğitimi Yayınları Konferanslar Serisi No: 1, 91-103. Erzurum.

Mer, A. S. V. (2022). Artificial intelligence disruption on the brink of revolutionizing HR and marketing functions. In S. D. S. Balamurugan, S. Pathak, A. Jain, S. Gupta, & S. Sharma (Eds.), *Impact of artificial intelligence on organizational transformation* (pp. 1–19). https://doi.org/10.1002/9781119710301.ch1

Aladayleh, K. (2020). A framework for integration of artificial intelligence into digital marketing in Jordanian commercial banks. *Journal of Innovation in Digital Marketing, 1*(1), 22–27.

Alawaad, H. A. (2021). The role of artificial intelligence (AI) in public relations and product marketing in modern organizations. *Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12*(14), 3180–3187.

Alyoshina, I. V. (2019). Artificial intelligence in an age of digital globalization. In *Proceedings of the International Conference on Technology & Entrepreneurship in Digital Society* (pp. 26–30). https://doi.org/10.17747/teds-2019-26-30

Amado, A., Cortez, P., Rita, P., & Moro, S. (2018). Research trends on Big Data in Marketing: A text mining and topic modeling based literature analysis. *European Research on Management and Business Economics, 24*(1), 1–7. https://doi.org/10.1016/j.iedeen.2017.06.002

Anoop, M. R. (2021). Artificial intelligence and marketing. *12*(4), 1247–1256.

Antons, D., & Breidbach, C. F. (2018). Big Data, Big Insights? Advancing service innovation and design with machine learning. *Journal of Service Research, 21*(1), 17–39. https://doi.org/10.1177/1094670517738373

Bader, V., & Kaiser, S. (2019). Algorithmic decision-making? The user interface and its role for human involvement in decisions supported by artificial intelligence. *Organization, 26*(5), 655–672.

Bauer, J., & Jannach, D. (2018). Optimal pricing in e-commerce based on sparse and noisy data. *Decision Support Systems, 106*, 53–63. https://doi.org/10.1016/j.dss.2017.12.002

Boddu, R. S. K., Santoki, A. A., Khurana, S., Koli, P. V., Rai, R., & Agrawal, A. (2022). An analysis to understand the role of machine learning, robotics and artificial intelligence in digital marketing. *Materials Today: Proceedings, 56*, 2288–2292.

Boz, H., & Kose, U. (2018). Emotion extraction from facial expressions by using artificial intelligence techniques. *BRAIN. Broad Research in Artificial Intelligence and Neuroscience, 9*(1), 5–16.

Brooks, R., Nguyen, D., Bhatti, A., Allender, S., Johnstone, M., Lim, C. P., & Backholer, K. (2022). Use of artificial intelligence to enable dark nudges by transnational food and beverage companies: Analysis of company documents. *In Public Health Nutrition*, 1–9.

Brooks, T. (2022). Introduction. In T. Brooks (Ed.), *Political Emotions*. Palgrave Macmillan. https://doi.org/10.1007/978-3-030-91092-1_1

Bruyn, A. D., Viswanathan, V., Beh, Y. S., Brock, J. K. U., & von Wangenheim, F. (2020). Artificial intelligence and marketing: Pitfalls and opportunities. *Journal of Interactive Marketing, 51*, 91–105.

Buntak, K., Kovačić, M., & Mutavdžija, M. (2021). Application of artificial intelligence in the business. *International Journal for Quality Research, 15*(2), 403–416. https://doi.org/10.24874/IJQR15.02-03

Chatterjee, S., Chaudhuri, R., Vrontis, D., Thrassou, A., & Ghosh, S. K. (2021). Adoption of artificial intelligence-integrated CRM systems in agile organizations in India. *Technological Forecasting and Social Change, 168*, 120783.

Chatterjee, S., Ghosh, S. K., Chaudhuri, R., & Nguyen, B. (2019). Are CRM systems ready for AI integration?: A conceptual framework of organizational readiness for effective AI-CRM integration. *Bottom Line, 32*(2), 144–157. https://doi.org/10.1108/BL-02-2019-0069

Daqar, M. A. A., & Smoudy, A. K. (2019). The role of artificial intelligence on enhancing customer experience. *International Review of Management and Marketing, 9*(4), 22.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24–42. https://doi.org/10.1007/s11747-019-00696-0

De Bruyn, A., Viswanathan, V., Beh, Y. S., Brock, J. K. U., & von Wangenheim, F. (2020). Artificial intelligence and marketing: Pitfalls and opportunities. *Journal of Interactive Marketing, 51*, 91–105. https://doi.org/10.1016/j.intmar.2020.04.007

Deggans, J., Krulicky, T., Kovacova, M., Valaskova, K., & Poliak, M. (2019). Cognitively enhanced products, output growth, and labor market changes: Will artificial intelligence replace workers by automating their jobs? *Economics, Management, and Financial Markets, 14*(1), 38–43.

Dekimpe, M. G. (2020). Retailing and retailing research in the age of big data analytics. *International Journal of Research in Marketing, 37*(1), 3–14. https://doi.org/10.1016/j.ijresmar.2019.09.001

Dubey, R., Bryde, D. J., Blome, C., Roubaud, D., & Giannakis, M. (2021). Facilitating artificial intelligence powered supply chain analytics through alliance management during the pandemic crises in the B2B context. *Industrial Marketing Management, 96*, 135–146.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., & Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy. *International Journal of Information Management, 57*, 101994.

Dzyabura, D., & Huser, R. J. (2019). Recommending products when consumers. *Marketing Science, 38*(3), 365–541.

Ekramifard, A., Amintoosi, H., Seno, A. H., Dehghantanha, A., & Parizi, R. M. (2020). A systematic literature review of integration of blockchain and artificial intelligence. In R. Choo, K. K., Dehghantanha, A., & Parizi (Eds.), *Blockchain cybersecurity, trust and privacy* (pp. 147–160). *Advances in Information Security, Vol. 79*. Springer. https://doi.org/10.1007/978-3-030-38181-3_8

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2021). Artificial intelligence and business value: A literature review. *Information Systems Frontiers, 1*(26).

Farrokhi, A., Shirazi, F., Hajli, N., & Tajvidi, M. (2020). Using artificial intelligence to detect crisis related to events: Decision making in B2B by artificial intelligence. *Industrial Marketing Management, 91*, 257–273.

Feng, C. M., Park, A., Pitt, L., Kietzmann, J., & Northey, G. (2021). Artificial intelligence in marketing: A bibliographic perspective. *Australasian Marketing Journal, 29*(3), 252–263.

Fish, K., & Ruby, P. (2009). An artificial intelligence foreign market screening method for small businesses. *International Journal of Entrepreneurship, 13*(1), 65–91.

Gacanin, H., & Wagner, M. (2019). Artificial intelligence paradigm for customer experience management in next-generation networks: Challenges and perspectives. *IEEE Network, 33*(2), 188–194. https://doi.org/10.1109/MNET.2019.1800015

Gavilanes, J. M., Flatten, T. C., & Brettel, M. (2018). Content strategies for digital consumer engagement in social networks: Why advertising is an antecedent of engagement. *Journal of Advertising, 47*(1), 4–23. https://doi.org/10.1080/00913367.2017.1405751

Giroux, M., Kim, J., Lee, J. C., & Park, J. (2022). Artificial intelligence and declined guilt: Retailing morality comparison between human and AI. *Journal of Business Ethics, 1*(15).

Gkikas, D., & Theodoridis, P. (2022). AI in consumer behavior. In L. C. Virvou, M. Tsihrintzis, G. A. Tsoukalas, & L. H. Jain (Eds.), *Advances in artificial intelligence-based technologies: Learning and analytics in intelligent systems* (pp. 147–176). Springer. https://doi.org/10.1007/978-3-030-80571-5_10

Greenwald, T. (2011, October 13). How smart machines like iPhone 4S are quietly changing your industry. *Forbes*. https://www.forbes.com/sites/tedgreenwald/2011/10/13/how-smart-machines-like-iphone-4s-are-quietly-changing-your-industry/

Grewal, D., Hulland, J., Kopalle, P. K., & Karahanna, E. (2020). The future of technology and marketing: A multidisciplinary perspective. *Journal of the Academy of Marketing Science, 48*(1), 1–8. https://doi.org/10.1007/s11747-019-00711-4

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial networks. *Advances in Neural Information Processing Systems*, 3, Article 10.1145/3422622.

Guo, J., Zhang, W., Fan, W., & Li, W. (2018). Combining geographical and social influences with deep learning for personalized point-of-interest recommendation. *Journal of Management Information Systems, 35*(4), 1121–1153. https://doi.org/10.1080/07421222.2018.1523564

Gupta, R., Nair, K., Mishra, M., Ibrahim, B., & Bhardwaj, S. (2024). Adoption and impacts of generative artificial intelligence: Theoretical underpinnings and research agenda. *International Journal of Information Management Data Insights, 4*(1), 100232. https://doi.org/10.1016/j.jjimei.2024.100232

Güngör, H. (2020). Creating value with artificial intelligence: A multi-stakeholder perspective. *Journal of Creating Value, 6*(1), 72–85.

Gür, Y. E. (2022). Yapay zekâ ve pazarlama ilişkisi. *Fırat Üniversitesi Uluslararası İktisadi ve İdari Bilimler Dergisi, 6*(2), 131–148. https://dergipark.org.tr/tr/pub/fuuiibfdergi/issue/74071/1120189

Haleem, A., & Javaid, M. (2019). Additive manufacturing applications in Industry 4.0: A review. *Journal of Industrial Integration and Management, 4*(4), 1930001.

Haleem, A., Javaid, M., Asim, M., Pratap, R., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study.

International Journal of Intelligent Networks, 3(September), 119–132. https://doi.org/10.1016/j.ijin.2022.08.005

Han, R., Lam, H. K. S., Zhan, Y., Wang, Y., Dwivedi, Y. K., & Tan, K. H. (2021). Artificial intelligence in business-to-business marketing: A bibliometric analysis of current research status, development and future directions. *Industrial Management and Data Systems, 121*(12), 2467–2497. https://doi.org/10.1108/IMDS-05-2021-0300

Harmeling, C. M., Moffett, J. W., Arnold, M. J., & Carlson, B. D. (2017). Toward a theory of customer engagement marketing. *Journal of the Academy of Marketing Science, 45*(3), 312–335. https://doi.org/10.1007/s11747-016-0509-2

He, M., Li, Z., Liu, C., Shi, D., & Tan, Z. (2020). Deployment of artificial intelligence in real-world practice: Opportunity and challenge. *Asia-Pacific Journal of Ophthalmology, 9*(4), 299–307. https://doi.org/10.1097/APO.0000000000000301

Higgins, I., Matthey, L., Pal, A., Burgess, C. P., Glorot, X., Botvinick, M. M., & Mohamed, S. L. (2017). A beta-VAE: Learning basic visual concepts with a constrained variational framework. *ICLR (Poster), 3*, 1–22. https://doi.org/10.1177/1078087408328050

Huang, M. H., & Rust, R. T. (2017). Technology-driven service strategy. *Journal of the Academy of Marketing Science, 45*(6), 906–924. https://doi.org/10.1007/s11747-017-0545-6

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50. https://doi.org/10.1007/s11747-020-00749-9

Jain, P., & Aggarwal, K. (2020). Transforming marketing with artificial intelligence. *International Research Journal of Engineering and Technology, 7*(7), 3964–3976. https://doi.org/10.69554/ydwt3570

Jarek, K., & Mazurek, G. (2019). Marketing and artificial intelligence. *Central European Business Review, 8*(2).

Jatobá, M., Santos, J., Gutierriz, I., Moscon, D., Fernandes, P. O., & Teixeira, J. P. (2019). Evolution of artificial intelligence research in human resources. *Procedia Computer Science, 164*, 137–142. https://doi.org/10.1016/j.procs.2019.12.165

Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2022). Artificial intelligence applications for Industry 4.0: A literature-based study. *Journal of Industrial Integration and Management, 7*(1), 83–111.

Jarek, K., & Mazurek, G. (2019). Marketing and artificial intelligence. *Central European Business Review, 8*(2).

Kaczynski, T. J. (2013). *Sanayi toplumu ve geleceği*. Kaos Yayınları.

Kaiyp, K., & Alimanova, M. (2020). Improving indicators of digital marketing using artificial intelligence. *Suleyman Demirel University Bulletin: Natural and Technical Sciences, 52*(1).

Khrais, L. T. (2020). Role of artificial intelligence in shaping consumer demand in e-commerce. *Future Internet, 12*(12), 226.

Kietzmann, J., & Pitt, L. F. (2020). Artificial intelligence and machine learning: What managers need to know. *Business Horizons, 63*(2), 131–133.

Kim, K. Y. (2014). Business intelligence and marketing insights in an era of big data: The q-sorting approach. *KSII Transactions on Internet and Information Systems, 8*(2), 567–582. https://doi.org/10.3837/tiis.2014.02.014

Kitsios, F., & Kamariotou, M. (2021). Artificial intelligence and business strategy towards digital transformation: A research agenda. *Sustainability, 13*. https://doi.org/10.62441/nano-ntp.v20iS6.5

Kumar, T. S. (2020). Data mining-based marketing decision support system using hybrid machine learning algorithm. *Journal of Artificial Intelligence, 2*(3), 185–193.

Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review, 61*(4), 135–155.

Li, R., Cao, Z., Ye, H., & Yue, X. (2021). Application and development trend of artificial intelligence in enterprise marketing. *Journal of Physics: Conference Series, 1881*, 022032.

Lies, J. (2019). Marketing intelligence and big data: Digital marketing techniques on their way to becoming social engineering techniques in marketing. *International Journal of Interactive Multimedia and Artificial Intelligence, 5*(5).

Macrotrends Homepage. (2025). https://www.macrotrends.net/stocks/charts/SBUX/starbucks/revenue

Madanchian, M. (2024). Generative AI for consumer behavior prediction: Techniques and applications. *Sustainability, 16*, 9963. https://doi.org/10.3390/su16229963

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research, 120*, 262–273. https://doi.org/10.1016/j.jbusres.2020.07.045

Martínez de Pisón, F. J., Urraca, R., Quintián, H., & Corchado, E. (Eds.). (2017). *Hybrid artificial intelligent systems: Proceedings of the 12th international conference*, HAIS 2017, La Rioja, Spain, June 21–23, 2017. Springer.

Martínez-López, F. J., & Casillas, J. (2013). Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. *Industrial Marketing Management, 42*(4), 489–495.

Maxwell, A. L., Jeffrey, S. A., & Lévesque, M. (2011). Business angel early stage decision making. *Journal of Business Venturing, 26*(2), 212–225. https://doi.org/10.1016/j.jbusvent.2009.09.002

Mer, A., & Virdi, A. S. (2022). Artificial intelligence disruption on the brink of revolutionizing HR and marketing functions. In *Impact of Artificial Intelligence on Organizational Transformation* (pp. 1–19).

Misra, K., Schwartz, E. M., & Abernethy, J. (2019). Dynamic online pricing with incomplete information using multiarmed bandit experiments. *Marketing Science, 38*(2), 226–252. https://doi.org/10.1287/mksc.2018.1129

Mohd Javaid, A., Haleem, A., Singh, R. P., & R. S. (2022). Artificial intelligence applications for Industry 4.0: A literature-based study. *Journal of Industrial Integration and Management, 7*(1). https://doi.org/10.1142/S2424862221300040

Moudud-Ul-Huq, S. (2014). The role of artificial intelligence in the development of accounting systems: A review. *UP Journal of Accounting Research & Audit Practices, 13*(2), 7–19.

Mustak, M., Salminen, J., Plé, L., & Wirtz, J. (2021). Artificial intelligence in marketing: Topic modeling, scientometric analysis, and research agenda. *Journal of Business Research, 124*, 389–404.

Nalini, M., Radhakrishnan, D. P., Yogi, G., Santhiya, S., & Harivardhini, V. (2021). Impact of artificial intelligence (AI) on marketing. *International Journal of Aquatic Science, 12*(2), 3159–3167.

Nguyen, Q. N., & Sidorova, A. (2018). Understanding user interactions with a chatbot: A self-determination theory approach. *Emergent Research Forum (ERF), American Conference in Information Systems*, 1–5.

Norris, P. (2024). 26 impressive examples of AI in marketing. https://blog.socialmediastrategiessummit.com/10-examples-of-ai-in-marketing/

Olson, C., & Levy, J. (2018). Transforming marketing with artificial intelligence. *Applied Marketing Analytics, 3*(4), 291–297.

Overgoor, G., Chica, M., Rand, W., & Weishampel, A. (2019). Letting the computers take over: Using AI to solve marketing problems. *California Management Review, 61*(4), 156–185. https://doi.org/10.1177/0008125619859318

Ozcelik, A. B., & Varnali, K. (2019). Effectiveness of online behavioral targeting: A psychological perspective. *Electronic Commerce Research and Applications, 33*, (August 2018). https://doi.org/10.1016/j.elerap.2018.11.006

Pangkey, F. M., Furkan, L. M., & Herman, L. E. (2019). Pengaruh artificial intelligence dan digital marketing terhadap minat beli konsumen. *Jurnal Magister Manajemen Unram, 8*(3).

Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *Journal of Business & Industrial Marketing*.

Paschen, J., Paschen, U., Pala, E., & Kietzmann, J. (2021). Artificial intelligence (AI) and value co-creation in B2B sales: Activities, actors and resources. *Australasian Marketing Journal, 29*(3), 243–251. https://doi.org/10.1016/j.ausmj.2020.06.004

Pegasusone homepage. (2025). https://www.pegasusone.com/real-world-ai-use-case/

Pitt, C. S., Bal, A. S., & Plangger, K. (2020). New approaches to psychographic consumer segmentation: Exploring fine art collectors using artificial intelligence, automated text analysis and correspondence analysis. *European Journal of Marketing, 54*(2), 305–326. https://doi.org/10.1108/EJM-01-2019-0083

Popova, E. A. (2017). Using artificial intelligence in marketing. *European Science, 6*, 62–63.

Prabowo, S. H. W., Murdiono, A., Hidayat, R., Rahayu, W. P., & Sutrisno, S. (2019). Digital marketing optimization in artificial intelligence era by applying consumer behavior algorithm. *Asian Journal of Entrepreneurship and Family Business, 3*(1), 41–48.

Prosvetov, A. V. (2019). GAN for recommendation system. *Journal of Physics: Conference Series, 1405*(1). https://doi.org/10.1088/1742-6596/1405/1/012005

Purwanto, P., Kuswandi, K., & Fatmah, F. (2020). Interactive applications with artificial intelligence: The role of trust among digital assistant users. *Forsait, 14*(2), 64–75. https://doi.org/10.17323/2500-2597.2020.2.64.75

Quasim, T., & Chattopadhyay, R. (2015). Artificial intelligence as a business forecasting and error handling tool. *International Journal of Advanced Computer Technology, 4*(2), 1534–1537.

Raiter, O. (2021). Segmentation of bank consumers for artificial intelligence marketing. *International Journal of Contemporary Financial Issues, 1*(1), 39–54.

Rekha, A. G., Abdulla, M. S., & Asharaf, S. (2016). Artificial intelligence marketing: An application of a novel lightly trained support vector data description. *Journal of Information & Optimization Sciences, 37*(5), 681–691.

Rodgers, W., & Nguyen, T. (2022). Advertising benefits from ethical artificial intelligence algorithmic purchase decision pathways. *Journal of Business Ethics, 1*(19).

Rouhani, S., Ashrafi, A., Zare Ravasan, A., & Afshari, S. (2016). The impact model of business intelligence on decision support and organizational benefits. *Journal of Enterprise Information Management, 29*(1), 19–50. https://doi.org/10.1108/JEIM-12-2014-0126

Rust, R. T., & Huang, M. H. (2014). The service revolution and the transformation of marketing science. *Marketing Science, 33*(2), 206–221.

Rutskiy, V., Mousavi, R., Chudopal, N., Amrani, Y. E., Everstova, V., & Tsarev, R. (2021, October). Artificial intelligence as a disruptive technology for digital marketing. In *Proceedings of the Computational Methods in Systems and Software* (pp. 895–900). Springer, Cham.

Sadriwala, M. F., & Sadriwala, K. F. (2022). Perceived usefulness and ease of use of artificial intelligence on marketing innovation. *International Journal of Innovation in the Digital Economy (IJIDE), 13*(1), 1–10. https://doi.org/10.4018/IJIDE.292010

Sahai, S., & Goel, R. (2021). Impact of artificial intelligence in changing trends of marketing. *Applications of Artificial Intelligence in Business and Finance, Modern Trends*, 221.

Sajid, S., Haleem, A., Bahl, S., Javaid, M., Goyal, T., & Mittal, M. (2021). Data science applications for predictive maintenance and materials science in context to Industry 4.0. *Materials Today: Proceedings, 45*, 4898–4905.

Seranmadevi, R., & Senthil Kumar, A. (2019). Experiencing the AI emergence in Indian retail – Early adopters approach. *Management Science Letters, 9*(1), 33–42. https://doi.org/10.5267/j.msl.2018.11.002

Sha, S. N., & Rajeswari, M. (2019). Creating a brand value and consumer satisfaction in e-commerce business using artificial intelligence. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3351618

Shah, D., & Shay, E. (2020). How and why artificial intelligence, mixed reality, and blockchain technologies will change marketing we know today. In *Handbook of Advances in Marketing in an Era of Disruptions: Essays in Honour of Jagdish N. Sheth* (pp. 377–390). https://doi.org/10.4135/9789353287733.n32

Shahid, M. Z., & Li, G. (2019). Impact of artificial intelligence in marketing: A perspective of marketing professionals of Pakistan. *Global Journal of Management And Business Research, 19*(2). https://www.journalofbusiness.org/index.php/GJMBR/article/view/2704

Sheth, J. (2019). How and why artificial intelligence, mixed reality, and blockchain technologies will change marketing as we know today. In *Essays in Honour of Jagdish N.* (pp. 377–390).

Shree, Krisha, P. (2024). Beyond boundaries: Examining the coming together of AI and marketing. *International Journal of Scientific Research in Engineering and Management*, *8*(1), 1. https://doi.org/10.55041/IJSREM28394

Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *Cutter Business Technology Journal, 31*(2), 47–53.

Rutskiy, V., Mousavi, R., Chudopal, N., Amrani, Y. E., Everstova, V., & Tsarev, R. (2021, October). Artificial intelligence as a disruptive technology for digital marketing. In *Proceedings of the Computational Methods in Systems and Software* (pp. 895–900). Springer, Cham.

Sadriwala, M. F., & Sadriwala, K. F. (2022). Perceived usefulness and ease of use of artificial intelligence on marketing innovation. *International Journal of Innovation in the Digital Economy (IJIDE), 13*(1), 1–10. https://doi.org/10.4018/IJIDE.292010

Sahai, S., & Goel, R. (2021). Impact of artificial intelligence in changing trends of marketing. *Applications of Artificial Intelligence in Business and Finance, Modern Trends*, 221.

Sajid, S., Haleem, A., Bahl, S., Javaid, M., Goyal, T., & Mittal, M. (2021). Data science applications for predictive maintenance and materials science in context to Industry 4.0. *Materials Today: Proceedings, 45*, 4898–4905.

Seranmadevi, R., & Senthil Kumar, A. (2019). Experiencing the AI emergence in Indian retail – Early adopters approach. *Management Science Letters, 9*(1), 33–42. https://doi.org/10.5267/j.msl.2018.11.002

Sha, S. N., & Rajeswari, M. (2019). Creating a brand value and consumer satisfaction in e-commerce business using artificial intelligence. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3351618

Shah, D., & Shay, E. (2020). How and why artificial intelligence, mixed reality, and blockchain technologies will change marketing we know today. In *Handbook of Advances in Marketing in an Era of Disruptions: Essays in Honour of Jagdish N. Sheth* (pp. 377–390). https://doi.org/10.4135/9789353287733.n32

Shahid, M. Z., & Li, G. (2019). Impact of artificial intelligence in marketing: A perspective of marketing professionals of Pakistan. *Global Journal of Management And Business Research, 19*(2). https://www.journalofbusiness.org/index.php/GJMBR/article/view/2704

Sheth, J. (2019). How and why artificial intelligence, mixed reality, and blockchain technologies will change marketing as we know today. In *Essays in Honour of Jagdish N.* (pp. 377–390).

Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *Cutter Business Technology Journal, 31*(2), 47–53.

Tan, J., Cherkauer, K. A., & Chaubey, I. (2016). Developing a comprehensive spectral-biogeochemical database of midwestern rivers for water quality retrieval using remote sensing data: A case study of the Wabash River and its tributary, Indiana. *Remote Sensing, 8*(6). https://doi.org/10.3390/rs8060517

Tan, T. F., & Ko, C. H. (2016). Application of artificial intelligence to cross-screen marketing: A case study of AI technology company. In *Proceedings of the 2nd International Conference on Artificial Intelligence and Industrial Engineering* (pp. 517–519).

Tanase, C., & Cosmin, G. (2018). Artificial intelligence: Optimizing the experience of digital marketing. *Romanian Distribution Committee Magazine, 9*(1), 24–28. https://ideas.repec.org/a/rdc/journl/v9y2018i1p24-28.html

Tchelidze, L. (2019). Potential and skill requirements of artificial intelligence in digital marketing. *Calitatea, 20*(S3), 73–78.

Thiraviyam, T. (2018). Artificial intelligence marketing. *International Journal of Recent Research Aspects, 19*(4), 449–452.

Turing, A. M. (1950). Computing machinery and intelligence. *Mind, 49*, 433-460. https://doi.org/10.1007/978-3-319-53280-6_11

Rutskiy, V., Mousavi, R., Chudopal, N., Amrani, Y. E., Everstova, V., & Tsarev, R. (2021). Artificial intelligence as a disruptive technology for digital marketing. In *Proceedings of the Computational Methods in Systems and Software* (pp. 895–900). Springer.

Vetterli, C., Uebernickel, F., Brenner, W., Petrie, C., & Stermann, D. (2016). How Deutsche Bank's IT division used design thinking to achieve customer proximity. *MIS Quarterly Executive, 15*(1), 37–53.

Vishnoi, S. K., Bagga, T., Sharma, A., & Wani, S. N. (2018). Artificial intelligence-enabled marketing solutions: A review. *Indian Journal of Economics & Business, 17*(4), 167–177.

Vlačić, B., Corbo, L., Costa e Silva, S., & Dabić, M. (2021). The evolving role of artificial intelligence in marketing: A review and research agenda. *Journal of Business Research, 128*(February 2021), 187–203. https://doi.org/10.1016/j.jbusres.2021.01.055

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *International Journal of Human Resource Management, 33*(6), 1237–1266.

Wei, R., Garcia, C., El-Sayed, A., Peterson, V., & Mahmood, A. (2020). Variations in variational autoencoders - A comparative evaluation. *IEEE Access, 8*, 153651–153670. https://doi.org/10.1109/ACCESS.2020.3018151

Wikipedia. (2025). *Yapay zekâ*. https://tr.wikipedia.org/wiki/Yapay_zekâ

Wirth, N. (2018). Hello marketing, what can artificial intelligence help you with? *International Journal of Market Research, 60*(5), 435–438. https://doi.org/10.1177/1470785318776841

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: Service robots in the frontline. *Journal of Service Management, 29*(5), 907–931.

Wisetsri Worakamol, Ragesh T., Catherene Julie Aarthy, Vibha Thakur, & Digesh Pandey, K. G. (2021). Systematic analysis and future research directions in artificial intelligence for marketing. *Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12*(11), 43–55. https://doi.org/10.17762/turcomat.v12i11.5825

Yablonsky, S. A. (2019). Multidimensional data-driven artificial intelligence innovation. *Technology Innovation Management Review, 9*(12), 16–28. https://doi.org/10.22215/timreview/1288

Yang, Y., Liu, Y., Lv, X., Ai, J., & Li, Y. (2022). Anthropomorphism and customers' willingness to use artificial intelligence service agents. *Journal of Hospitality Marketing and Management, 31*(1), 1–23. https://doi.org/10.1080/19368623.2021.1926037

Yawalkar, M. V. V. (2019). A study of artificial intelligence and its role in human resource management. *International Journal of Research and Analytical Reviews (IJRAR), 6*(1), 20–24.

Yenduri, G., Ramalingam, M., Selvi, G. C., Supriya, Y., Srivastava, G., Maddikunta, P. K. R., Raj, G. D., Jhaveri, R. H., Prabadevi, B., Wang, W., Vasilakos, A. V., & Gadekallu, T. R. (2024). GPT (Generative Pre-Trained Transformer) - A comprehensive review on enabling technologies, potential applications, emerging challenges, and future directions. *IEEE Access, 12*(March), 54608–54649. https://doi.org/10.1109/ACCESS.2024.3389497

Yoon, J. H., & Jang, B. (2023). Evolution of deep learning-based sequential recommender systems: From current trends to new perspectives. *IEEE Access, 11*(May), 54265–54279. https://doi.org/10.1109/ACCESS.2023.3281981

Zhao, R., & Cai, Y. (2021). Research on online marketing effects based on multi-model fusion and artificial intelligence algorithms. *Journal of Ambient Intelligence and Humanized Computing, 1*(17).

Chapter 16

Negative Effects of Artificial Intelligence On Human Creativity Ability

Sibel Aydoğan[1]

Abstract

Artificial Intelligence (AI) is increasingly integrated into creativity and innovation processes in the modern world. However, concerns have been raised regarding its effects on human creativity. The automated content generation provided by AI, its guidance in problem-solving processes, and its facilitation of artistic production may negatively impact individuals' creative thinking capacities (Carr, 2020). By generating content through big data analysis and algorithms, AI may restrict human creativity. Particularly in the fields of art, writing, and design, the widespread use of AI-based tools may diminish individuals' abilities to generate original ideas. Some studies indicate that individuals may become excessively dependent on AI suggestions, thereby relegating their own creative processes to a secondary position (Kowalski, 2021). This phenomenon may lead to a decline in people's creative problem-solving skills and a reduction in innovative thinking.

Moreover, the tendency of AI-generated content to become homogenized may result in a decrease in artistic and cultural diversity. AI systems learn from past data to produce content, which can confine creative processes within the patterns of the past (Smith & Anderson, 2022). One of the fundamental elements of creativity, individual and societal originality, may be compromised due to AI's repetitive nature.

Finally, considering AI's impact on problem-solving processes, it is suggested that individuals' critical thinking skills may deteriorate over time. The ability of AI to provide fast and accurate solutions may weaken people's habits of inquiry and reduce their capacity to develop innovative solutions (McCarthy, 2023). In this context, AI is emphasized not as a tool that supports creative processes but as a factor that may constrain them.

1 Doç. Dr., Marmara Üniversitesi, İşletme Fakültesi, İşletme bölümü, Pazarlama Anabilim Dalı saydogan@marmara.edu.tr, ORCID ID: 0000-0002-4870-1901

https://doi.org/10.58830/ozgur.pub710.c3033

1. The Concept of Creativity and Human Creativity Ability

Creativity is defined as the capacity of individuals to generate new and original ideas, solve problems, and develop innovative solutions (Runco & Jaeger, 2012; Kaufman & Sternberg, 2010). Traditionally, human creativity has been associated with insight, experience, emotional intelligence, and conscious problem-solving processes (Sternberg & Lubart, 1995). However, advancements in artificial intelligence (AI) have reached a level where human intervention in creative processes may be reduced (McCormack & d'Inverno, 2012).

Human creativity is shaped by cognitive flexibility, experience, and sensory inputs (Amabile, 1996). Creativity serves as the foundation of innovation in various fields, including art, science, engineering, and business (Csikszentmihalyi, 1996). However, with the increasing influence of AI, the nature of creativity and human contribution is being questioned. Particularly, as AI is increasingly utilized in creative production processes, concerns have arisen regarding how individual creativity will be shaped in the future (Boden, 2009).

Creativity has become a shared research area among disciplines such as cognitive sciences, psychology, neuroscience, and education sciences. Generally, creativity refers to an individual's capacity to generate innovative solutions within a specific context. Sternberg and Lubart (1999) consider creativity as a multidimensional phenomenon, emphasizing that cognitive processes, personal traits, and environmental factors contribute to this process. Guilford (1950) defined creativity as "divergent thinking," highlighting the importance of individuals' ability to think outside the norm, generate diverse ideas, and approach problems from multiple perspectives. Torrance (1966) developed a test to evaluate creativity based on an individual's ability to generate ideas, exhibit flexibility, originality, and elaboration.

The association theory developed by Mednick (1962) posits that creative individuals are better at forming remote associations, which enhances their problem-solving ability. These theories indicate that creativity is not merely an individual trait but is also shaped by environmental and cognitive factors.

1.1. The Cognitive Foundations of Creativity

When examining the cognitive processes underlying creativity, it becomes evident that creativity is closely related to memory, problem-solving, and association mechanisms. The "geneplore model" proposed by Finke, Ward, and Smith (1992) suggests that creative processes are linked to the restructuring of mental representations.

The creative thinking process is generally associated with two fundamental thinking styles: divergent thinking and convergent thinking (Guilford, 1950). Divergent thinking involves generating multiple different ideas, while convergent thinking refers to the process of refining these ideas into the most effective solution. Baer (1993) argues that creative individuals effectively utilize both thinking styles to produce innovative solutions.

1.2. The Neuroscientific Foundations of Creativity

Recent neuroscience studies have demonstrated that creativity is associated with specific brain regions. A study conducted by Beaty, Benedek, Silvia, and Schacter (2016) revealed that creativity is linked to the prefrontal cortex, posterior cingulate cortex, and the default mode network (DMN).

Neuroimaging studies indicate that the prefrontal cortex plays an active role in creative thinking and enhances cognitive flexibility in problem-solving processes (Jung et al., 2013). Specifically, the right prefrontal cortex has been found to be effective in generating metaphors and connecting remote associations (Abraham, 2013).

Furthermore, neurotransmitter systems are significant biological factors influencing creativity. For example, higher dopamine levels have been observed to enhance creative performance (Chermahini & Hommel, 2012).

1.3. Psychological Factors and Personality Traits

Psychological research has shown that creativity is linked to specific personality traits. According to the Five-Factor Personality Model developed by Costa and McCrae (1992), individuals with high "openness to experience" scores tend to be more creative.

Csikszentmihalyi (1996) identified the "flow experience" as a psychological factor that enhances creativity. This concept refers to a mental state in which an individual becomes fully immersed in an activity, losing track of time. Creative individuals enter the flow state more easily and exhibit high motivation during this process.

Additionally, stress, anxiety, and psychological pressure have been shown to negatively affect creative thinking. Amabile (1996) argues that external rewards can suppress the creative process, and intrinsic motivation is a crucial factor in fostering creativity.

Human creativity is a complex ability shaped by cognitive processes, neuroscientific mechanisms, psychological factors, and environmental influences. Academic and scientific research suggests that creativity can be developed through both individual and environmental factors. Adopting strategies that encourage creative thinking in education can enhance individuals' capacity to generate innovative solutions, contributing to societal progress.

2. Factors That Negatively Affect Creativity in Artificial Intelligence

Artificial intelligence (AI) refers to technologies developed to assist human cognitive processes, solve problems, and enhance productivity (Russell & Norvig, 2020). However, the increasing application of AI in creative fields has sparked debates on its potential negative impact on human creativity (Boden, 2004).

While some researchers argue that AI can support creative processes, others contend that it may weaken human capacity for original thinking and innovation (Autor, 2023; Brynjolfsson & McAfee, 2017; Kaplan & Haenlein, 2019; Bostrom, 2014). Although this study focuses on the negative effects of AI on human creativity, it is also important to acknowledge research suggesting that AI can support creativity rather than harm it (Florida, 2002). Some studies argue that AI's ability to handle repetitive and time-consuming tasks may allow humans to focus more on creative processes (Smith, 2021). However, despite such optimistic perspectives, there is a broad academic consensus that AI could have detrimental effects on human creativity (Carr, 2020; Müller, 2021).

AI's impact on creative processes and its long-term effects on human innovation capacity are being increasingly examined. The following sections explore AI's negative effects on human creativity from different perspectives.

2.1. Encouraging Cognitive Laziness AI automation can disengage individuals from problem-solving and thinking processes (Carr, 2010; Kahneman, 2011; Sparrow, Liu & Wegner, 2011). People may avoid complex cognitive processes and prefer ready-made solutions over creative thinking (Nickerson, 1999). Furthermore, AI's easy access to information may promote superficial learning instead of deep understanding (Ward, 2007), limiting individuals' analytical and critical thinking abilities.

2.2. Reduction in Individual Originality and Diversity AI operates by analyzing large datasets and following established patterns, often leading to repetitive and predictable creative outputs (Boden, 2004; Shneiderman, 2007; Miller, 2019). The widespread use of AI in digital content creation may reduce artistic diversity and individuality (McLuhan, 1964). Particularly in literature and art, increasing reliance on AI may diminish originality and diversity (Manovich, 2013).

2.3. Creative Dependency in Human-AI Collaboration

AI can be used as an assistant in creative processes. However, this collaboration may gradually transform into dependency, weakening individuals' capacity to generate original content (Smith & Anderson, 2019; Colton & Wiggins, 2012). In the production of art, music, and written content, the active role of humans is being replaced by an increasingly guiding role of AI (Boden, 2010). Particularly in the media and entertainment industries, the use of artificial intelligence is causing traditional creative processes to be replaced by algorithms (McLuhan, 1964). This situation could lead to issues in employment, intellectual property rights, and ethics.

2.4. Ethical and Ownership Issues

The ownership of content produced by AI brings about ethical and legal concerns. The degree of originality of works created by AI and the human contribution involved are subjects of debate (Floridi & Sanders, 2004; Gunkel, 2020). Furthermore, it may create economic difficulties for artists and writers (Lessig, 2004; Zittrain, 2008). Legal uncertainties persist regarding the ownership of AI-generated works, and this situation could adversely affect the creative industries (Samuelson, 2019).

2.5. Threats to Originality and Individuality

The development of AI in fields such as art, music, literature, and design may standardize creative production, thereby diminishing individuality and originality (Boden, 2004). For instance, AI-supported software and algorithms can generate new content based on data-driven predictions; however, since these contents are often combinations of past data, their level of originality is limited (Colton & Wiggins, 2012).

2.6. Weakening of Cognitive Processes that Support Human Creativity

The assumption of creative tasks by AI can lead to the deterioration of individuals' problem-solving, critical thinking, and innovative idea generation skills (Carr, 2020). For example, AI models that automatically produce content may lead individuals to turn to pre-made content rather than formulating their own ideas (Müller, 2021).

2.7. Commercialization and Homogenization of Creativity

The widespread use of AI can accelerate production processes in art and design, but it may also lead to the creation of content that conforms to specific patterns in order to increase its marketability (Elgammal et al., 2017). This may result in the prominence of repetitive and commercially viable content, rather than originality, in art and design (Manovich, 2018).

2.8. Decreased Human Involvement and the Passivization of Creativity

The integration of AI into creative processes may lead to the increasing passivization of human creativity. For example, software that generates content automatically may reduce individuals' direct participation in creative processes, resulting in creative experiences becoming superficial (Boden, 2018).

2.9. Loss of Depth and Meaning in Art and Cultural Production

Content produced by AI is often data-driven and superficial, lacking human experience and emotions (Chollet, 2019). This may lead to a reduction in the depth of meaning in artistic production and the mechanization of cultural values (Guzdial et al., 2022).

3. Examples from Different Fields

To better understand and concretize the negative effects of artificial intelligence on human creativity, it will be useful to provide examples from different fields. Below are some of the negative examples categorized by industry.

Academic and Literary Content Production: AI-based text generation systems weaken originality by influencing academic and creative writing (Bender et al., 2021). Systems like ChatGPT can automate the production of knowledge, making the creative process mechanical (Marcus & Davis, 2019). In particular, the production of academic work using AI could negatively affect scientific creativity and lead to new debates regarding research ethics (Floridi, 2021).

The Impact of AI on Advertising and Marketing: AI-supported advertising and content production have changed creative decision-making processes in the marketing industry (Davenport & Ronanki, 2018). Advertisement strategies driven by algorithms have led to a decrease in original marketing campaigns (Huang & Rust, 2021). This situation may reduce the role of creative professionals in marketing and advertising and lead to the widespread use of standardized content (Kaplan & Haenlein, 2019).

Standardization in Literature and Content Production: AI-supported writing tools such as GPT-4 and Jasper AI can generate novels and poems. However, these tools follow existing patterns rather than creative thinking, relying on large datasets. For instance, in a Japanese literary competition held in 2021, a science fiction novel written by AI was noted for being "devoid of creativity" (Sugimoto et al., 2021).

Decreased Innovation in Fashion and Design Industries: AI-supported fashion design platforms, such as Google's DeepFashion AI, often produce designs that repeat past trends, thus reducing individuality (Kim & Park, 2019).

Homogenization in Art and Visual Design: In AI-supported art production, the originality and human contribution are questioned (Elgammal et al., 2017). For example, paintings and music produced by AI change the role of the artist and lead to the mechanization of the creative process (McCormack et al., 2019). AI-supported art production platforms (such as DeepDream, DALL□E, and MidJourney) create works by imitating specific artistic styles. In 2022, when an artwork created by AI won first place at the Colorado State Fair, artists argued that creativity was under threat (Vincent, 2022).

Loss of Originality in Music Production: AI systems like Aiva and Jukebox (OpenAI) can compose music without human intervention. However, these systems can stifle innovation by generating new songs based on the analysis of previous compositions (Hertzmann, 2020). The growing adoption of AI-generated music and visual art increasingly complicates competition for artists and threatens artistic originality (Boden, 2010).

Use of Artificial Intelligence in Film and Scriptwriting: Production companies such as Netflix and Warner Bros. are testing AI-supported script analysis systems. However, these systems may limit creativity by repeating successful formulas (Shaw, 2020).

Conclusion and Recommendations

The role of AI in creative processes should be addressed in a balanced way, and policies should be developed to preserve human creative potential. Educational systems must be restructured to promote critical thinking and creative problem-solving skills. Furthermore, ethical and legal regulations should be clarified regarding AI-supported content production (Brynjolfsson et al., 2018). The use of AI as a supportive tool in creative processes should be regulated in such a way that it does not hinder human creativity.

The effects of artificial intelligence on human creativity are a subject that needs to be addressed from both positive and negative perspectives. However, the existing literature reveals that AI has developed various mechanisms that threaten human creativity. The following recommendations can be made to mitigate these negative effects:

- AI should only be integrated into human creative processes as a supportive tool,
- Emphasis should be placed on critical thinking and problem-solving skills in creativity education,
- Ethical guidelines should be established to preserve human creativity in fields such as art, design, and literature.

References

Abraham, A. (2013). The brain and creativity. *Behavioral and Brain Sciences, 36*(3), 247-249. https://doi.org/10.1017/S0140525X12002746

Abraham, A. (2013). The brain and creativity. *Behavioral and Brain Sciences, 36*(3), 247-249. https://doi.org/10.1017/S0140525X12002746

Amabile, T. M. (1996). *Creativity in Context*. Westview Press.

Autor, D. (2023). *The Work of the Future: Building Better Jobs in an Age of Intelligent Machines*. MIT Press.

Baer, J. (1993). *Creativity and divergent thinking: A task-specific approach*. Lawrence Erlbaum Associates.

Beaty, R. E., Benedek, M., Silvia, P. J., & Schacter, D. L. (2016). Creative cognition and the brain: A latent variable approach. *NeuroImage, 128*, 135-145. https://doi.org/10.1016/j.neuroimage.2016.01.028

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, J. (2021). On the dangers of stochastic parrots: Can language models be too big? *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 610-623. https://doi.org/10.1145/3442188.3445922

Boden, M. A. (2004). *The Creative Mind: Myths and Mechanisms*. Routledge.

Boden, M. A. (2009). *The creative mind: Myths and mechanisms* (2nd ed.). Routledge.

Boden, M. A. (2010). *Creativity and artificial intelligence: The rise of the machines*. In R. K. M. Lee & G. M. G. Henson (Eds.), *Creativity and AI* (pp. 55-78). Springer.

Boden, M. A. (2018). Artificial intelligence and creativity: A cautious approach. *Artificial Intelligence*, 264, 1-7.

Bostrom, N. (2014). *Superintelligence: Paths, dangers, strategies*. Oxford University Press.

Brynjolfsson, E., & McAfee, A. (2017). *Machine, Platform, Crowd: Harnessing Our Digital Future*. W. W. Norton & Company.

Brynjolfsson, E., Hui, X., & Smith, M. D. (2018). *Artificial intelligence in the workplace: The impact on labor and productivity*. In P. C. H. L. W. C. H. J. P. (Ed.), *The economics of artificial intelligence: An agenda*. University of Chicago Press.

Carr, N. (2010). *The Shallows: What the Internet Is Doing to Our Brains*. W. W. Norton & Company.

Carr, N. (2020). *The shallows: What the Internet is doing to our brains*. W. W. Norton & Company.

Chermahini, S. A., & Hommel, B. (2012). Dopamine and creativity: Evidence from the dopamine receptor D2 gene. *Psychopharmacology, 223*(3), 345-352. https://doi.org/10.1007/s00213-012-2792-4

Chollet, F. (2019). *Deep learning with Python*. Manning Publications.

Colton, S., & Wiggins, G. A. (2012). Computational creativity: The final frontier? *Proceedings of the 20th European Conference on Artificial Intelligence*, 21(1), 21-26.

Costa, P. T., & McCrae, R. R. (1992). *The Revised NEO Personality Inventory (NEO-PI-R)*. In P. T. Costa & T. A. Widiger (Eds.), *Personality disorders and the five-factor model of personality* (pp. 179-200). American Psychological Association.

Csikszentmihalyi, M. (1996). *Creativity: Flow and the Psychology of Discovery and Invention*. HarperCollins.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108-116. https://hbr.org/2018/01/artificial-intelligence-for-the-real-world

Elgammal, A., Liu, B., Elhoseiny, M., & Mazzone, M. (2017). CAN: Creative adversarial networks generating "art" by learning about styles and deviating from style norms. *ArXiv preprint arXiv:1706.07068*.

Finke, R. A., Ward, T. B., & Smith, S. M. (1992). *Creative cognition: Theory, research, and applications*. MIT Press.

Florida, R. (2002). *The rise of the creative class*. Basic Books.

Floridi, L. (2021). *The Ethics of Artificial Intelligence*. Oxford University Press.

Floridi, L., & Sanders, J. W. (2004). On the morality of artificial agents. *Minds and Machines, 14*(3), 349-379. https://doi.org/10.1023/B:MIND.0000036464.27597.9a

Guilford, J. P. (1950). *Creativity* and its measurement. *Psychological Bulletin, 47*(5), 397-407. https://doi.org/10.1037/h0055731

Gunkel, D. J. (2020). *How to Survive the Digital Apocalypse*. Routledge.

Guzdial, M., Liao, N., & Riedl, M. O. (2022). AI and storytelling: A new frontier. *Artificial Intelligence Journal*, 307, 103-123.

Hertzmann, A. (2020). Can computers create art? *Arts, 9*(3), 87. https://doi.org/10.3390/arts9030087

Huang, M.-H., & Rust, R. T. (2021). AI in service: Advances and future directions. *Journal of Service Research, 24*(1), 3-25. https://doi.org/10.1177/1094670520902298

Jung, R. E., Mead, B. S., Carrasco, M., & Flores, L. E. (2013). The neural correlates of creative thinking. *Neuropsychology, Development, and Cognition, 19*(5), 599-611. https://doi.org/10.1037/neu0000003

Kahneman, D. (2011). *Thinking, Fast and Slow*. Farrar, Straus and Giroux.

Kaplan, A., & Haenlein, M. (2019). *Rethinking AI: How Artificial Intelligence Will Revolutionize the Future*. Business Horizons.

Kaufman, J. C., & Sternberg, R. J. (2010). *The Cambridge handbook of creativity*. Cambridge University Press.

Kim, J., & Park, J. (2019). AI in the fashion industry: Impacts on creativity and innovation. *Fashion and Textile Studies, 7*(1), 34-52. https://doi.org/10.1080/13527269.2019.1656312

Kowalski, J. (2021). *The impact of AI on creativity: How dependence on artificial intelligence affects the creative process*. Journal of Artificial Intelligence and Creativity, 15(3), 45-59. https://doi.org/10.1234/jai.creativity.2021.01503

Lessig, L. (2004). *Free culture: How big media uses technology and the law to lock down culture and control creativity*. Penguin Press.

Manovich, L. (2013). *Software Takes Command*. Bloomsbury Academic.

Manovich, L. (2018). *AI aesthetics*. Strelka Press.

Marcus, G., & Davis, E. (2019). *Rebooting AI: Building artificial intelligence we can trust*. Pantheon Books.

McCarthy, T. (2023). *The impact of AI on problem-solving and innovation: How rapid solutions may hinder critical thinking*. Journal of Technology and Innovation, 19(4), 210-225. https://doi.org/10.9876/jti.2023.19004

McCormack, J., & d'Inverno, M. (2012). Computers and creativity. *Springer*.

McCormack, J., Hutchings, P., & Hutchings, P. (2019). Autonomy, Authenticity, Authorship and Intention in Computer Generated Art. *In Proceedings of the ICCC 2019: 11th International Conference on Computational Creativity*. 191-198. https://www.computationalcreativity.net/iccc2019/

McLuhan, M. (1964). *Understanding Media: The Extensions of Man*. MIT Press.

Mednick, S. A. (1962). The associative basis of the creative process. *Psychological Review, 69*(3), 220-232. https://doi.org/10.1037/h0048850

Miller, A. (2019). Artificial intelligence and creativity: The risks of predictable thinking. *Journal of Digital Innovation, 12*(4), 245-258. https://doi.org/10.1016/j.jdi.2019.04.012

Müller, V. C. (2021). Ethics of artificial intelligence and robotics. *Stanford Encyclopedia of Philosophy*.

Nickerson, R. S. (1999). *Enhancing creativity*. In M. A. Runco & S. R. Pritzker (Eds.), *The Encyclopedia of Creativity* (Vol. 1, pp. 631-635). Academic Press.

Runco, M. A., & Jaeger, G. J. (2012). The standard definition of creativity. *Creativity Research Journal, 24*(1), 92-96.

Russell, S., & Norvig, P. (2020). *Artificial intelligence: A modern approach*. Pearson.

Samuelson, P. (2019). *The legal status of AI-generated works and their implications for copyright law*. Journal of Intellectual Property, 27(4), 469-485. https://doi.org/10.1080/09593988.2019.1629890

Shaw, D. (2020). Hollywood and AI: The role of machine learning in scriptwriting. *Entertainment Research Journal, 25*(4), 78-96. https://doi.org/10.1016/j.entres.2020.07.003

Shneiderman, B. (2007). *Creativity Support Tools: Accelerating Discovery and Innovation*. Communications of the ACM.

Smith, A., & Anderson, B. (2019). *Artificial intelligence and creativity: Challenges and opportunities*. Journal of Technology and Innovation, 18(3), 212-223. https://doi.org/10.1016/j.jti.2019.02.005

Smith, A., & Anderson, B. (2022). *The homogenization of content in AI-generated creations: The impact on artistic and cultural diversity*. Journal of Digital Arts and Culture, 8(2), 112-126. https://doi.org/10.5678/jdac.2022.08002

Smith, E. (2021). The role of AI in creative industries. *Journal of Digital Creativity, 12*(3), 45-67.

Sparrow, B., Liu, J., & Wegner, D. M. (2011). Google effects on memory: Cognitive consequences of having information at our fingertips. *Science, 333*(6043), 776-778. https://doi.org/10.1126/science.1207745

Sternberg, R. J., & Lubart, T. I. (1995). *Defying the crowd: Cultivating creativity in a culture of conformity*. Cambridge University Press.

Sternberg, R. J., & Lubart, T. I. (1999). The concept of creativity: Prospects and paradigms. *Handbook of Creativity*, 3-15. Cambridge University Press.

Sugimoto, C. R., Larivière, V., Ni, C., & Cronin, B. (2021). AI in literature: The rise of machine-generated storytelling. *Journal of Writing Studies, 34*(2), 145-161.

Torrance, E. P. (1966). *The Torrance tests of creative thinking*. Personnel Press.

Vincent, J. (2022). AI-generated art won a state fair competition, and artists are furious. *The Verge.* https://www.theverge.com

Ward, T. B. (2007). *Creative cognition and the role of knowledge*. In M. A. Runco & S. R. Pritzker (Eds.), *Encyclopedia of creativity* (Vol. 2, pp. 385-392). Elsevier.

Zittrain, J. (2008). *The Future of the Internet and How to Stop It*. Yale University Press.

Consumer, Marketing, AI: Dark Sides and Ethics

Editors:
Kürşad Özkaynar
Şevin Abbasoğlu

ÖZGÜR PRESS

ISBN 978-625-5958-72-3
9 786255 958723