Chapter 6

The Misleading Power of AI-Powered Automation

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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

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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."

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