# Yönetim Bilişim Sistemleri Alanında Yenilikçi Çözümler ve Güncel Yaklaşımlar – II

**Editör: Doç. Dr. Vahid SİNAP**

ÖZGÜR YAYINLARI

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ÖZGÜR
YAYINLARI

# Ön Söz

“Yönetim Bilişim Sistemleri Alanında Yenilikçi Çözümler ve Güncel Yaklaşımlar – II” başlıklı bu eser, ilk kitabın sağladığı akademik birikimi ve etki alanını daha da genişleterek, dijital dönüşüm çağının dinamiklerini derinlemesine ele alan bir devam niteliğindedir. Teknoloji, yönetim ve toplumsal değişimin kesişiminde yer alan Yönetim Bilişim Sistemleri (YBS) alanı, işletme süreçlerinden karar alma biçimlerine, etik anlayıştan ekonomik refaha kadar geniş bir etki alanına sahip stratejik bir disiplin hâline gelmiştir. Bu kitap, tam da bu dönüşümün çok katmanlı yapısını anlamaya yönelik bütüncül bir çerçeve sunmaktadır.

Eserde yer alan bölümler, yapay zekâ uygulamalarından dijital hazırlık ve ekonomik refah ilişkisine, veri odaklı karar destek sistemlerinden sürdürülebilir kent lojistiği ve dijital davranış analizlerine kadar uzanan geniş bir yelpazede, günümüzün öncelikli araştırma alanlarını kapsamaktadır. Her çalışma, YBS’nin güncel sorun alanlarına nasıl çözüm üretebileceğini somut veriler ve analitik yöntemlerle ortaya koymakta, disiplinin sürekli yenilenen doğasına ışık tutmaktadır. Bu yönüyle eser hem teknolojik gelişmeleri hem de bunların örgütsel, toplumsal ve bireysel düzeydeki etkilerini kavramak isteyen araştırmacılar için değerli bir kaynak niteliği taşımaktadır.

Kitapta sunulan çalışmalar, yönetim bilişiminin teknik uzmanlığın ötesine geçerek etik duyarlılık, yenilikçilik, sürdürülebilirlik ve insani değerlerle şekillenen bütüncül bir düşünme biçimini temsil ettiğini ortaya koymaktadır. Dijital çağın gerektirdiği yeni beceriler, veriyle desteklenen karar alma kültürü, algoritmik yönetişim ve etik farkındalık gibi konular, eser boyunca bütünsel bir anlayışla ele alınmıştır.

Bu ikinci cilt, birincisinde başlatılan akademik ve düşünsel hattı sürdürmekte, geleceğin bilgi toplumunda etkin, güvenilir ve sorumlu bilişim sistemlerinin nasıl inşa edilebileceğine dair tartışmaları derinleştirmektedir. Yönetim Bilişim Sistemleri alanında çalışan akademisyenler, öğrenciler ve uygulayıcılar için yeni ufuklar açmasını, araştırmalara yön verecek bir referans kaynağı oluşturmasını dilerim.

Doç. Dr. Vahid SİNAP

Editör

# İçindekiler

Bölüm 1

# Dijital Hazırlık ve Ekonomik Refah: Bilgi ve İletişim Teknolojileri Hazırlık Endeksinin Kişi Başına Düşen Gayri Safi Yurtiçi Hasıla Üzerindeki Etkisi

**Rana Şen Doğan**[1]

**Murat Doğan**[2]

**Özet**

Dijital hazırlık, ülkelerin rekabet gücü ve ekonomik refahını şekillendiren temel bir belirleyicidir. Bu bölüm, dijital altyapı, insan kaynağı, yönetişim ve dijitalleşmenin somut çıktılarının birlikte ele alındığı Ağ Hazırlık Endeksi ile kişi başına düşen gayrisafi yurt içi hasıla arasındaki ilişkiyi incelemeyi amaçlamaktadır. 2024 yılına ait 134 ülke verisi kullanılmıştır. Gelir bilgileri Dünya Bankası'ndan, endeks puanları Portulans Enstitüsü'nden alınmıştır. Çalışmanın yöntemi, endeks ile gelir arasındaki ilişkinin yönünü ve gücünü sınayan karşılaştırmalı bir ilişki çözümlemesine dayanmaktadır. Ölçüm kalitesinin yeterliliği gözden geçirilmiş, sonuçların tutarlılığı alternatif tanımlamalar ve duyarlılık kontrolleriyle denetlenmiştir. Dijital hazırlık düzeyi yüksek ülkelerin kişi başına gelir bakımından belirgin bir üstünlüğe sahip olduğunu ortaya koymaktadır. Gelirdeki farklılıkların kayda değer bir bölümü dijital hazırlıkla ilişkilendirilebilmekte; dört alt boyutun (Teknoloji, İnsan, Yönetişim, Etki) birbirini tamamlayarak ilerlemesi hâlinde refah artışı güçlenmektedir. Altyapı yatırımlarının beceri geliştirme, güven ve düzenleme, veri yönetişimi ve kapsayıcı uygulamalarla birlikte tasarlanması gerektiği anlaşılmaktadır. Bu çalışma, dijital erişim ve ağ yatırımlarını dört alt boyutunu eş zamanlı yürüten ülkelerin daha yüksek ekonomik refah ürettiğini göstermektedir.

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## 1. GİRİŞ

Dijitalleşme, ekonomiyi ve toplumu dönüştüren temel bir kalkınma alanıdır. Bilgi ve İletişim Teknolojileri (BİT), yalnızca teknolojik ilerlemeyi değil, aynı zamanda üretim süreçlerinden kamu hizmetlerine ve bireylerin yaşam kalitesine kadar pek çok alanı etkileyen çok boyutlu bir unsur hâline gelmiştir. Bu bağlamda, dijital kapasitenin artırılmasına yönelik politikalar, sürdürülebilir ekonomik büyümenin sağlanmasında stratejik bir rol üstlenmektedir.

Dijitalleşmenin ekonomik çıktılar üzerindeki etkisini analiz etmek amacıyla geliştirilen çeşitli göstergeler, politika yapıcılar ve akademik çevreler için önemli bir referans noktası sunmaktadır. Bu göstergeler arasında öne çıkan Bilgi ve İletişim Teknolojileri Hazırlık Endeksi (BİTHE - Network Readiness Index - NRI), dijital hazırlık düzeyini dört temel boyut (Teknoloji, İnsan, Yönetişim ve Etki) ölçer. Amaç, ülkelerin dijital dönüşüme ilişkin uyumunu izlemektir. BİTHE, yalnızca altyapısal donanımı değil, dijital beceriler, yönetişim kalitesi ve dijital hizmetlerin toplumsal etkilerini de dikkate alan kapsamlı bir ölçüm çerçevesi sunmaktadır.

Bilgi ve İletişim Teknolojilerinin ekonomik büyüme üzerindeki olumlu etkisi, çok sayıda ampirik çalışmada vurgulanmaktadır (Ganju vd., 2016; Niebel, 2018). Ancak söz konusu ilişkinin bağlamdan bağımsız değildir. Ülkelerin dijitalleşme düzeyi, yönetişim yapıları ve ekonomik gelişmişlik düzeyi gibi çeşitli yapısal faktörlerden etkilenebileceği de literatürde sıklıkla dile getirilmektedir (Fernández-Portillo vd., 2020). Bu nedenle, dijital hazırlığın kişi başına düşen gelir (Gayri Safi Yurtiçi Hasıla GSYİH/kişi – GDP per capita) düzeyi üzerinden ele alınan ekonomik refah üzerindeki etkisinin, daha kapsamlı modeller ve güncel verilerle değerlendirilmesi hem kuramsal hem de uygulamalı açıdan önem taşımaktadır.

Bu çalışma, dijitalleşmenin ekonomik refah üzerindeki etkisini BİTHE çerçevesinde bütüncül bir yaklaşımla incelemektedir. Dört temel boyuttan oluşan BİTHE, bu çalışmada yüksek düzey yansıtıcı bir yapı olarak modellenmiştir. Söz konusu boyutların GSYİH/kişi üzerindeki etkisi Kısmi En Küçük Kareler Yapısal Eşitlik Modellemesi (PLS-SEM) ile analiz edilmiştir. 2024 yılına ait 134 ülkenin BİTHE ve GSYİH/kişi verileriyle yürütülen analiz, dijitalleşmenin yalnızca altyapı yatırımlarıyla sınırlı olmayan; yönetişim kalitesi ve insan sermayesi gibi sosyal bileşenlerle bütünleştiğinde ekonomik çıktılar üzerinde güçlü ve anlamlı etkiler yarattığını ortaya koymaktadır.

Mevcut literatürde genellikle BİTHE alt boyutlarının ayrı ayrı ele alındığı görülürken, bu çalışma endeksin özgün yapısını koruyarak bütüncül bir modelle ampirik olarak test eden sayılı araştırmalardan biridir. Bulgular, yalnızca teorik geçerliği yüksek bir dijitalleşme endeksinin ekonomik refah üzerindeki dönüştürücü gücünü ortaya koymakla kalmamakta; aynı zamanda politika yapıcılar için senkronize ve hedef odaklı dijital dönüşüm stratejilerinin tasarlanmasına yönelik somut kanıtlar sunmaktadır. Bu yönüyle araştırma, dijitalleşme ve kalkınma literatürüne hem yöntemsel hem de uygulamalı düzeyde özgün katkılar sağlamayı amaçlamaktadır.

## 2. LİTERATÜR TARAMASI VE TEORİK ARKA PLAN

### 2.1. Dijitalleşme ve Ekonomik Kalkınma

BİT, ülkelerin dijital dönüşüm düzeylerini etkileyen temel bir yapısal unsur olarak değerlendirilmektedir. Bit yalnızca teknolojik bir yenilik alanı değil, aynı zamanda üretim süreçlerinden kamu hizmetlerine, bireysel refahtan yönetişim kalitesine kadar uzanan bir dönüşüm sürecini temsil etmektedir (Dobrota vd., 2012; Gomes vd., 2022). Literatürün büyük bölümü, BİT yatırımlarının ekonomik büyüme ve kalkınma üzerinde olumlu etkiler doğurduğunu ortaya koymakla birlikte, bu ilişkinin bağlamsal faktörlere bağlı olarak farklılaşabileceği ve bazı durumlarda sınırlı ya da etkisiz sonuçlar doğurabileceği yönünde bulgulara da yer verilmektedir (Fernández-Portillo vd., 2020).

Mevcut literatür, BİT yatırımlarının ekonomik büyümeyi desteklediği kadar, GSYİH/kişi gibi doğrudan bireysel refahı temsil eden göstergeler üzerinde de olumlu etkiler yaratabileceğini ortaya koymaktadır (Ganju vd., 2016; Niebel, 2018). Aynı zamanda, BİT'in üretkenlik, verimlilik ve genel ekonomik refah üzerindeki etkileri de vurgulanmaktadır (Ganju vd., 2016; Pradhan vd., 2018). Bu etkilerin gelişmiş ve gelişmekte olan ülkelerde benzer düzeylerde ortaya çıkabileceğini öne süren çalışmalar bulunmakla birlikte (Niebel, 2018), sektörel kullanım yoğunluğu ve insanî gelişim düzeyinin belirleyici olduğu yönünde karşıt bulgulara da rastlanmaktadır (Hoz-Rosales vd., 2019; Gholami vd., 2010).

BİT'in ekonomik etkileri özellikle altyapı ve genişbant teknolojileri bağlamında da ele alınmaktadır. Genişbant ağların yaygınlığı, mobil teknolojilerin erişilebilirliği ve dijital bağlantılılık düzeyinin artması, ekonomik fırsatların genişlemesine doğrudan katkı sağlamaktadır (Edquist vd., 2018). Benzer şekilde, COVID-19 pandemisi gibi küresel kriz dönemlerinde dijital altyapının gelişmişliği, ülkelerin ekonomik dirençlerini artırmış ve üretim kayıplarını sınırlı düzeyde tutmalarını sağlamıştır (Chen vd., 2024).

Dijitalleşmenin etkisi yalnızca altyapı yatırımlarıyla sınırlı kalmamakta, insan sermayesi ve inovasyon süreçleriyle de yakından ilişkilidir. BİT, bilgiye erişimi kolaylaştırmakta, iş gücünün niteliğini artırmakta ve inovasyon kapasitesine katkı sağlamaktadır (Vu vd., 2020). Öte yandan, dijital kamu hizmetlerinin (e-devlet) yönetişim kalitesine, kaynak kullanım etkinliğine ve kamu hizmetlerinin sunumuna katkıda bulunduğu da sıklıkla vurgulanmaktadır. Bu süreçlerde kamu-özel sektör iş birlikleri (PPP), dijital dönüşümün hızlandırılmasında önemli bir araç olarak değerlendirilmektedir (Mayer-Schönberger & Lazer, 2007).

Genel olarak literatür, dijitalleşmenin ekonomik kalkınma üzerindeki etkisinin bağlamsal koşullara bağlı olarak değiştiğini göstermektedir. Bu etkide özellikle ülkelerin dijital altyapı düzeyi, insan sermayesi kapasitesi ve yönetişim yapılarının belirleyici rol oynadığı vurgulanmaktadır. Ancak dijitalleşmenin ekonomik çıktılar üzerindeki etkisini anlamak, yalnızca altyapısal yatırımların değil, aynı zamanda sosyal ve yönetsel bileşenlerin de hesaba katıldığı ölçüm araçlarını gerektirmektedir.

Bu kapsamda, BİTHE, dijital dönüşümün ekonomik ve toplumsal etkilerini bir bütün olarak değerlendirebilen, kuramsal temeli sağlam ve karşılaştırılabilir uluslararası veriler sunan bütüncül bir göstergedir. Bir sonraki bölümde, bu çalışmanın temelini oluşturan BİTHE'nin yapısı ve analitik çerçevesi ayrıntılı biçimde ele alınacaktır.

### 2.2. Bilgi ve İletişim Teknolojileri Hazırlık Endeksi ve Yapısı

Dijital dönüşümün ekonomik ve toplumsal etkilerini sağlıklı biçimde analiz edebilmek için ülkelerin dijital kapasitesini ölçen, kavramsal tutarlılığı yüksek ve çok boyutlu göstergelere ihtiyaç duyulmaktadır. Bu çerçevede, BİTHE, ülkelerin dijitalleşme düzeyini yalnızca teknolojik altyapı üzerinden değil, aynı zamanda insan sermayesi, yönetişim kapasitesi ve toplumsal etki gibi sosyal boyutlar üzerinden de değerlendiren bütüncül bir ölçüm sistemidir (Tokmergenova & Dobos, 2024).

BİTHE 2024, dört temel boyut etrafında yapılandırılmıştır. Her bir boyut üç alt göstergeden oluşmaktadır. Ölçek toplamda on iki alt boyut endeksin analitik yapısını oluşturmaktadır. Bu alt boyutlar şunlardır:

- **Teknoloji**: Erişim, İçerik, Gelecek Teknolojileri
- **İnsan**: Bireyler, İşletmeler, Hükümetler

- **Yönetişim**: Güven, Düzenleme, Kapsayıcılık
- **Etki**: Ekonomi, Yaşam Kalitesi, SDG Katkısı (Sürdürülebilir Kalkınma Amaçları)

Tüm alt boyutlar eşit ağırlıkta değerlendirilerek genel endeks puanı oluşturulmaktadır (Tokmergenova & Dobos, 2024).

Endeksin oluşturulmasında gösterge seçimi; teorik geçerlilik, güncel literatür desteği, uzman görüşleri ve ülkeler arası karşılaştırılabilir veri mevcudiyeti gibi kriterler doğrultusunda şekillendirilmiştir (Dutta & Lanvin, 2024). Bu yönüyle BİTHE, yalnızca dijitalleşme seviyesini değil, bu dijitalleşmenin ekonomik ve toplumsal sonuçlarını da değerlendirmeye imkân tanımaktadır.

BİTHE ve benzeri endeksler, dijital dönüşümün düzeyini karşılaştırmalı olarak izlemek isteyen politika yapıcılar, araştırmacılar ve uluslararası kurumlar tarafından yaygın biçimde kullanılmaktadır (Dobrota vd., 2012). Özellikle "Etki" boyutu, BİTHE'nin diğer teknik göstergelerden ayrışmasını sağlamaktadır. Bu boyut, dijitalleşmenin toplumsal refah, dijital kapsayıcılık, sürdürülebilir kalkınma ve kamu değerine katkısı gibi daha kapsamlı çıktılar üzerindeki etkilerini değerlendirme kapasitesiyle öne çıkmaktadır (Tokmergenova & Dobos, 2024).

### 2.3. Literatürde Kullanılan Yöntemler, Politika Çıkarımları ve Araştırma Boşlukları

BİT ile ekonomik büyüme arasındaki ilişki, farklı yöntemsel yaklaşımlar ve politika odaklı değerlendirmelerle uzun süredir araştırma gündeminde yer almaktadır. Ampirik çalışmalarda, BİT göstergeleri ile ekonomik çıktılar arasındaki ilişkileri incelemek amacıyla Temel Bileşenler Analizi (PCA), I-distance yöntemi (Dobrota vd., 2012), panel veri regresyonları ve Granger nedensellik analizleri (Niebel, 2018; Pradhan vd., 2018) gibi çeşitli istatistiksel tekniklerden yararlanılmıştır. Son dönemde ise dijitalleşmeyi çok boyutlu bir çerçevede ele alan endekslerin, özellikle de BİTHE gibi yapısal olarak katmanlı göstergelerin, PLS-SEM yöntemiyle analiz edilmesine yönelik çalışmalar artış göstermektedir (Tokmergenova & Dobos, 2024).

Dijital dönüşümün ekonomik çıktılar üzerindeki etkisini analiz eden çalışmalarda yalnızca altyapı yatırımları değil, aynı zamanda insan sermayesi, dijital yönetişim kapasitesi, dijital katılım düzeyi ve yaşam kalitesi gibi sosyal bileşenler de belirleyici değişkenler olarak öne çıkmaktadır. Bu bağlamda, Dünya Ekonomik Forumu (Baller vd., 2016; Dutta vd., 2015) ve Kirkman vd. (2002) tarafından geliştirilen politika çerçevelerinde; teknolojik altyapının güçlendirilmesinin yanı sıra dijital becerilerin artırılması, yaşam boyu öğrenme uygulamalarının teşvik edilmesi ve dijital düzenleyici çerçevenin geliştirilmesi gibi öneriler sıklıkla dile getirilmektedir.

Bununla birlikte, mevcut literatürde bazı yapısal boşlukların varlığı dikkat çekmektedir. Dijitalleşmenin ekonomik etkilerini daha güçlü nedensellik ilişkileriyle test edebilmek için gerekli olan uzunlamasına veri setlerinin sınırlı oluşu, çok düzeyli endekslerin hiyerarşik yapılarının analitik modellerde yeterince dikkate alınmaması ve sektörel düzeydeki farklılaşmaların yeterince incelenmemesi bu boşluklar arasında öne çıkmaktadır (Chen vd., 2024; Shah & Krishnan, 2024). Özellikle, BİTHE gibi çok boyutlu ve bütünleşik endekslerin, ikinci düzey hiyerarşik yapılar temelinde modellenmesi gerektiği vurgulanmaktadır (Tokmergenova & Dobos, 2024).

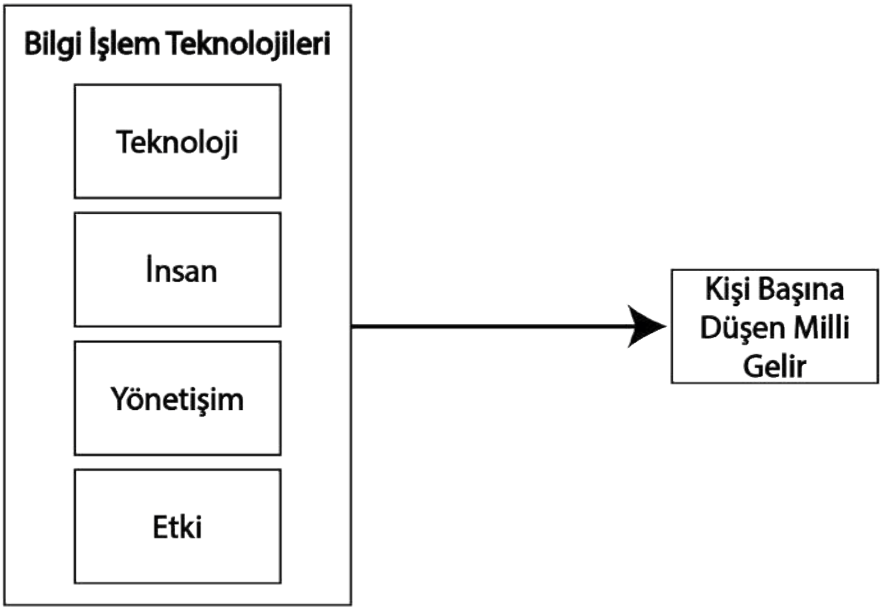
Bu bağlamda, mevcut çalışma, BİTHE'ın dört temel boyutunu yansıtıcı bir yapı altında ele alarak, dijitalleşmenin ekonomik çıktılar üzerindeki etkisini incelemiştir. Aynı zamanda çalışma dijitalleşme açısından bütüncül bir yaklaşım sergileyen sınırlı sayıdaki çalışmalardan biri olma özelliği taşımaktadır. Literatürde tanımlanan yöntemsel boşlukların tamamını kapsamamaktadır. Dijitalleşme endekslerinin çok boyutlu yapısını yapısal eşitlik modellemesiyle bütünleştirmesi bakımından önemli bir metodolojik katkı sunmaktadır. Çalışmanın diğer sınırlılıkları ve gelecek araştırmalar için öneriler ise sonuç bölümünde tartışılmıştır.

### 2.4. Araştırma Modeli ve Hipotezlerin Geliştirilmesi

Bu çalışma, BİT temelli dijitalleşme düzeyinin ekonomik büyüme üzerindeki etkisini BİTHE göstergeleri aracılığıyla değerlendirmektedir. BİTHE'ın dört temel bileşeni, dijital hazırlığın farklı yönlerini temsil etmektedir, bu boyutun GSYİH/kişi üzerindeki etkileri test edilmiştir. Yöntemsel olarak bu modelleme yaklaşımı, dijitalleşmenin boyutsal doğasını dikkate alarak çok düzeyli bir yapının makroekonomik çıktılarla ilişkisini ölçmeyi mümkün kılmaktadır. Buna göre hipotez 1 oluşturulmuştur. Bu hipotez, dijital altyapı, erişim ve ileri teknoloji yatırımlarının ekonomik büyümeyi destekleyici etkisini vurgulayan literatürle örtüşmektedir (Ganju vd., 2016; Niebel, 2018).

**H1:** BİTHE, GSYİH/kişi üzerinde pozitif ve anlamlı bir etkiye sahiptir.

Tüm bu varsayımlar doğrultusunda oluşturulan araştırma modelinin görsel temsili aşağıda sunulmuştur:




***Şekil 1: Araştırma Modeli***

## 3. YÖNTEM

### 3.1. Araştırma Tasarımı

Bu çalışma, BİT ekonomik çıktılar üzerindeki etkisini yapısal bir model aracılığıyla incelemeyi amaçlamaktadır. Bu doğrultuda, araştırma modeli, BİTHE göstergelerinin alt boyutları ile GSYİH/kişi arasındaki ilişkileri açıklamak üzere kurgulanmıştır. BİTHE, yansıtıcı bir yapı olarak modellenmiş ve dört ana bileşen üzerinden ölçülmüştür.

Bu yaklaşım, yalnızca nedensel ilişkilerin test edilmesini değil, aynı zamanda BİTHE göstergelerinin ekonomik büyüme üzerindeki katkısının daha bütüncül biçimde anlaşılmasını da mümkün kılmaktadır.

### 3.2. Veri Seti ve Örneklem

Çalışmanın örneklemini, 134 ülke oluşturmaktadır. Bu ülkeler, dijital dönüşüm ve ekonomik kalkınma düzeylerinin karşılaştırmalı analizine olanak tanıyan veri çeşitliliği ve güvenilirliği açısından tercih edilmiştir. Çalışmada kullanılan veriler, 2024 yılına ait yatay kesit biçimde derlenmiştir.

Veri yılı olarak 2024 tercih edilmiştir. Bu tercih hem BİTHE hem GSYİH/kişi verilerinin eksiksiz ve karşılaştırılabilir biçimde sunulan en güncel yıl olmasıdır.

Bağımlı değişken olan GSYİH/kişi, Dünya Bankası veri tabanından; bağımsız değişkenleri oluşturan BİTHE boyutları ise "Portulans Institute" tarafından yayımlanan "Network Readiness Index" raporundan alınmıştır. Her bir BİTHE boyutu, endekste sunulan bileşik skorlar üzerinden temsil edilmiştir.

Bu örneklem yapısı ve değişken seçimi, dijitalleşme ile ekonomik performans arasındaki yapısal ilişkiyi istatistiksel olarak test etmeye ve genellenebilir sonuçlar üretmeye olanak tanımaktadır.

### 3.3. Veri Analizi

Verilerin analizinde, PLS-SEM tercih edilmiştir. Bu yöntem, özellikle karmaşık modellerde ve görece küçük örneklem büyüklüklerinde, normallik varsayımı gerektirmemesi ve yordayıcı güce odaklanması gibi avantajlar nedeniyle uygun bulunmuştur. Analiz süreci, SmartPLS yazılımı ile yürütülmüştür.

Modelleme süreci iki temel aşamadan oluşmuştur. Öncelikle, ölçüm modelinin geçerlilik ve güvenilirliği değerlendirilmiştir. İkinci aşamada, hipotez testlerine yönelik yapısal model analizi gerçekleştirilmiştir. Bu kapsamda değişkenlerin model üzerindeki katkı düzeyleri analiz edilmiştir. Bu adımlar, modelin standart ölçütleri karşıladığını ve teorik olarak tutarlı bir yapı oluşturduğunu dorulamaktadır.

## 4. BULGULAR

### 4.1. Ölçüm Modeli Bulguları

Bu çalışmada kullanılan ölçüm modelinin geçerliliği ve güvenilirliği dört temel kriter doğrultusunda değerlendirilmiştir. Bu kriterler gösterge yükleri, iç tutarlılık katsayıları, yakınsak geçerlik (convergent validity) ve ayrım geçerliğidir (discriminant validity).

Göstergeler ve Faktör Yükleri: BİTHE yapısının dört alt boyutunu temsil eden değişkenlerine ait faktör yükleri 0,939 ile 0,958 arasında değişmektedir. Literatürde $\geq 0{,}70$ olarak önerilen eşik değer dikkate alındığında, tüm göstergelerin yeterli düzeyde faktör yüküne sahip olduğu görülmektedir. Özellikle Teknoloji ($\lambda = 0{,}958$) ve Yönetişim ($\lambda = 0{,}951$) göstergelerinin 0,95'in üzerindeki yüksek yükleri, bu değişkenlerin BİTHE yapısıyla güçlü bir yakınsama içinde olduğunu ortaya koymaktadır. Ayrıca tüm alt boyutların ağırlıklarının birbirine yakın olması (Teknoloji = 0,270; Etki = 0,269; Yönetişim = 0,278; İnsan = 0,238), dört alt boyutun BİTHE endeksini dengeli biçimde temsil ettiğine işaret etmektedir.

İç Tutarlılık ve Yakınsak Geçerlik: İç tutarlılığı değerlendirmek üzere hesaplanan güvenilirlik katsayıları oldukça yüksek düzeydedir. Cronbach's $\alpha$ değeri 0,962, $\rho A$ değeri 0,965 ve birleşik güvenilirlik ($\rho C$) değeri 0,972 olarak hesaplanmıştır. Bu değerler, ölçüm aracının mükemmel düzeyde içsel tutarlılığa sahip olduğunu göstermektedir ($\alpha > 0,90$). Yakınsak geçerliği değerlendirmek için kullanılan ortalama varyans açıklaması (AVE) değeri ise 0,898 olarak bulunmuştur. AVE > 0,50 koşulunun fazlasıyla sağlanması, kullanılan göstergelerin, temsil ettikleri yapının varyansını yüksek oranda açıkladığını doğrulamaktadır.

Ayrım Geçerliği: Ayrım geçerliği iki farklı yöntemle test edilmiştir. İlk olarak HTMT (heterotrait-monotrait ratio) değeri, BİTHE ile GSYİH/kişi arasındaki ilişki için 0,812 olarak bulunmuş ve önerilen < 0,85 sınırının altında kalmıştır. Bu sonuç, yapıların birbirinden yeterince ayrıştığını göstermektedir. İkinci olarak, Fornell–Larcker kriterine göre her yapının AVE karekökü, diğer yapılarla olan tüm korelasyon değerlerinden daha büyüktür. Bu bulgular birlikte ele alındığında, ölçüm modelinin hem geçerli hem de güvenilir olduğu ve yapılar arasında ayrım yapılabildiği sonucuna ulaşılmıştır. Bu da yapısal model analizlerinin sağlam temellere dayandığını ortaya koymaktadır.

### 4.2. Yapısal Model Bulguları

Yapısal eşitlik modelinin analizinde, BİTHE ile GSYİH/kişi arasındaki ilişkinin gücü, yönü ve açıklayıcılığı kapsamlı biçimde değerlendirilmiştir. Bulgular, modelin istatistiksel olarak anlamlı ve yüksek derecede uyumlu olduğunu göstermektedir.

**Yol Katsayıları ve Etki Büyüklüğü:** Yapısal modelde, BİTHE'den GSYİH/kişi'ye doğru olan doğrudan etkinin yol katsayısı $\beta = 0,799$ olarak bulunmuştur ve bu ilişki istatistiksel olarak yüksek düzeyde anlamlıdır ($p < 0,001$). Bu sonuç, BİTHE'nin bir birimlik artışın, kişi başına düşen gelirde yaklaşık 0,8 birimlik artışa yol açtığını göstermektedir. Etki büyüklüğü $f^2 = 1,771$ olarak hesaplanmıştır. Cohen'in (1988) sınıflamasına göre $f^2 > 0,35$ "büyük" etkiyi temsil ederken, bu değerin çok üzerinde kalan bulgumuz, BİTHE'nin ekonomik çıktılar üzerindeki etkisinin oldukça güçlü olduğunu ortaya koymaktadır. Bu durum, BİTHE'nin dijital dönüşümle ekonomik refah arasındaki köprü rolünü vurgulayan literatürle tutarlıdır.

**Açıklanan Varyans ve Kollinearite:** Bağımlı değişken olan GSYİH/kişi için hesaplanan determinasyon katsayısı ($R^2$) 0,639'dur. Bu değer, modelin kişi başına düşen gelirdeki varyansın %63,9'unu açıkladığını göstermektedir. $R^2$ değerinin 0,33–0,67 aralığında olması, orta-yüksek düzeyde bir açıklayıcılığa karşılık gelmekte ve BİTHE'nin ekonomik performans üzerindeki güçlü belirleyiciliğini desteklemektedir.

Kollinearite sorununu test etmek amacıyla incelenen iç VIF değerleri tüm yapılar için 1,0 olarak bulunmuş ve bu durum, modelde herhangi bir çoklu doğrusal ilişki problemi olmadığını göstermiştir. Yansıtıcı göstergelere ait dış VIF değerlerinin 4,8–7,1 aralığında kalması ise literatürde kabul edilen <10 eşik değerine uygundur.

**Model Uyum İstatistikleri:** Modelin genel uyumuna ilişkin değerlendirmelerde SRMR ve NFI indeksleri dikkate alınmıştır. Hesaplanan SRMR = 0,031 olup, önerilen 0,08 sınırının oldukça altında kalmaktadır. NFI değeri ise 0,948 olup, > 0,90 sınır değeri aşılmıştır. Bu bulgular, yapısal modelin gözlemlenen veriye yüksek düzeyde uyum sağladığını teyit etmektedir. Ayrıca, d_ULS ve d_G gibi model uyumu alternatif ölçütlerinin düşük değerler alması, tahmin edilen model ile doygun model arasındaki farkın oldukça sınırlı olduğunu göstermektedir. Sonuç olarak, geliştirilen model BİTHE'nin ekonomik çıktılar üzerindeki etkisini istatistiksel olarak güçlü, anlamlı ve güvenilir biçimde temsil etmektedir.

## 5. SONUÇ VE TARTIŞMALAR

Bu çalışma, BİTHE'nin dört temel boyutunu yansıtıcı biçimde modelleyerek dijital hazırlığın ekonomik refah üzerindeki etkisi değerlendirmiştir. Elde edilen bulgular, hem ölçüm hem de yapısal model düzeyinde yüksek geçerlik, güvenilirlik ve açıklama gücü ortaya koymuştur. Bu bölümde sonuçlar üç eksende tartışılmaktadır: (1) ekonomik çıkarımlar, (2) karşılaştırmalı değerlendirme ve literatür katkısı, (3) politika etkileri.

### 5.1 Ekonomik Çıkarım

Yapısal model sonuçları, BİTHE → GSYİH/kişi yolunun güçlü ve istatistiksel olarak anlamlıdır. Bu bulgu, ağ hazırlığındaki bir birimlik artışın, kişi başına düşen gelirde yaklaşık 0,8 birimlik artışla sonuçlanmaktadır. BİTHE'in makro iktisat literatüründe nadiren gözlenen ölçüde güçlü bir dönüştürücü rol üstlendiğini göstermektedir.

Model GSYİH/kişi varyansının %63,9'unun yalnızca BİTHE tarafından açıklandığını göstermekte; bu da dijital hazırlığın ekonomik büyüme için kritik bir kaldıraç işlevi gördüğünü ortaya koymaktadır. Çoklu doğrusal bağlantılar açısından kollinearite sorunu olmadığını doğrulamıştır. Modelin uyum istatistikleri, SEM modelinin gözlemlenen veriyle yüksek düzeyde örtüştüğünü teyit etmektedir.

Bu sonuçlar, dijital teknolojilerin yalnızca üretkenliği artırmakla kalmayıp doğrudan ekonomik çıktılara da katkı sunduğunu; dijital hazırlığın gelir yaratımı üzerindeki etkisinin istatistiksel olarak güçlü ve pratikte anlamlı olduğunu göstermektedir. BİTHE 2024 raporunda vurgulanan Dijital Kamu Özel Ortaklıklarının ekonomik büyümeyi tetikleyici rolü, bu ilişkinin sadece teknolojik değil, yönetişim ve insan sermayesi boyutlarıyla da bütüncül olduğunu göstermektedir.

### 5.2 Karşılaştırmalı Değerlendirme ve Literatür Katkısı

Çalışma, BİTHE'nin dört boyutlu özgün yapısını koruyarak oluşturulan yüksek düzey bir yapıyı modellemiş; boyutlar arasında yüksek faktör yükleri (0,939–0,958) ve dengeli ağırlıklar ($w \approx 0{,}24$–$0{,}28$) elde edilmiştir. Bu bulgular, BİTHE'in alt bileşenlerinin birbirini tamamlayarak ekonomik çıktılar üzerinde birlikte daha güçlü bir etki yarattığını göstermektedir.

Avrupa Komisyonu Ortak Araştırma Merkezi'nin 2024 yılı BİTHE denetimi de birleşik endeks sıralamalarının, tekil sütunlara göre %14–18 oranında daha farklı ve etkili sonuçlar ürettiğini raporlamıştır. Bu, çok boyutlu ve bütüncül modellemenin üstünlüğünü istatistiksel olarak da teyit etmektedir.

Öte yandan, mevcut literatürde BİTHE'nin bileşenleri çoğunlukla bağımsız değişken olarak incelenmekte; bütüncül yapının etkisi çoğu çalışmada ihmal edilmektedir. Yakın dönemde yapılan bazı Bayesian Belief Network temelli analizler dört sütun arasındaki karşılıklı bağımlılıkları olasılıksal çerçevede ele alarak bu boşluğu kapatmaya çalışmış; bu çalışma ise yapısal eşitlik modellemesiyle deterministik ve ölçülebilir bir çözüm sunmuştur. Bu yönüyle mevcut araştırma, BİTHE'nin teorik geçerliği ve ekonomik etki gücüne ilişkin literatüre nicel ve yöntemsel bir katkı sunmaktadır.

### 5.3 Politika Etkileri

Bulgular, dijital dönüşüm politikalarının entegre bir yaklaşımla tasarlanması gerektiğini göstermektedir. Yalnızca altyapıya değil, aynı zamanda insan sermayesi ve yönetişim reformları alanlarına eş zamanlı yatırım yapılması gerektiğini göstermektedir. Elde edilen bu çıktı yatırımın sürdürülebilir olmasını sağlayacaktır.

BİTHE 2024 raporunda da belirtildiği üzere, "İşletmeler" ve "Güven" alt boyutları, dijitalleşmenin etkili olabilmesi için kritik geçiş noktalarıdır. Bu nedenle, ülkeler:

- BİTHE'nin dört boyutunda denge gözeten dijital kalkınma planları oluşturmalı,
- Zayıf alanları hedefleyen "ağ hazırlığı paketleri" geliştirmeli,
- Dijital kamu özel ortaklıklarını artırmalı,
- Yaşam boyu öğrenme ve dijital beceri eğitimleriyle nitelikli iş gücü yetiştirmelidir.

Ayrıca, dijital uçurumun azaltılması (cinsiyet, bölge, gelir gibi farklar) uzun vadeli kalkınma açısından kritik öneme sahiptir. Evrensel hizmet fonları, hedefli sübvansiyonlar ve dijital kapsayıcılık programları, yalnızca ekonomik büyümeyi değil, eşitliği ve sürdürülebilirliği de destekleyecektir.

### 5.4. Sınırlılıklar ve Gelecek Çalışmalar için Öneriler

Bu çalışma, BİTHE'yi içeren bir model aracılığıyla analiz etmiştir. Elde edilen bulgular, dijital hazırlık düzeyindeki artışın kişi başına düşen gelir üzerinde son derece güçlü ve anlamlı bir etki yarattığını ortaya koymaktadır. Bununla birlikte, çalışmanın kapsamı ve yöntemi çerçevesinde bazı sınırlılıklar da bulunmaktadır. Bu noktalar, gelecek araştırmalar açısından değerli açılımlar sunma potansiyeli taşımaktadır.

İlk olarak, çalışma tek yıllık (2024) kesit verilerine dayanmaktadır. Bu durum, modeldeki ilişkilerin korelasyon düzeyinde değerlendirilmesine yol açmaktadır. Gelecekte uzunlamasına veri setlerinin kullanılması, dijital dönüşümün ekonomik çıktılar üzerindeki zaman içindeki etkilerinin daha güçlü biçimde test edilmesine olanak tanıyabilir. Özellikle panel veri analizleri veya zaman serisi teknikleri kullanılarak nedensel ilişkilerin incelenmesi, alana önemli katkılar sağlayacaktır.

İkinci olarak, çalışmada BİTHE yalnızca dört ana boyut üzerinden modellenmiştir. Oysa endeksin yapısı çok daha zengindir; 12 alt sütun ve 54 göstergeden oluşan çok katmanlı bir içerik barındırmaktadır. Bu açıdan, ilerleyen çalışmalarda ikinci düzey yapılarla (High-Order Constructs SEM) bu detayların modele entegre edilmesi, dijital hazırlığın bileşenlerinin göreli etkilerinin daha ayrıntılı şekilde anlaşılmasına katkı sunabilir. Bu tür bir yaklaşımın uygulanmasında, göstergeler arası yüksek korelasyonların yönetilebilmesi için boyut indirgeme tekniklerinin de dikkate alınması önerilmektedir.

Üçüncü olarak, dijitalleşmenin ekonomik refah üzerindeki etkisinin hangi süreçler aracılığıyla ortaya çıktığı bu çalışmanın kapsamı dışında kalmıştır. İnovasyon kapasitesi, insan gelişmişliği ya da eşitsizlik düzeyleri gibi aracı değişkenlerin bu ilişkide oynadığı rolün gelecek araştırmalarda ele alınması, dijitalleşmenin etkilerini daha açıklayıcı bir çerçevede değerlendirmeyi mümkün kılacaktır.

Son olarak, çalışmanın odağı makroekonomik düzeyde kurulmuş bir modele dayanmaktadır. Oysa dijital teknolojilerin sektörel düzeydeki etkileri farklılaşabilmektedir. Tarım, sanayi ve hizmet sektörleri gibi alanlarda dijitalleşmenin yansımalarının ayrı ayrı incelendiği çalışmalar, politika yapıcılar açısından daha hedefli çözüm önerileri geliştirilmesine imkân tanıyacaktır.

Bu öneriler doğrultusunda geliştirilecek çalışmalar, dijitalleşmenin kalkınma üzerindeki rolüne dair daha bütüncül ve derinlikli anlayışlar kazandırabilir. Böylelikle dijital dönüşüm politikalarının daha etkin ve kapsayıcı biçimde tasarlanmasına bilimsel bir zemin hazırlanabilir. Bu bağlamda, mevcut çalışmanın BİTHE'nin dört temel boyutuyla bütüncül bir yapıda ele alarak ekonomik refah üzerindeki etkisini ampirik olarak ortaya koyması, literatürdeki boşlukların giderilmesine ve gelecek araştırmalara yön gösterilmesine katkı sağlamaktadır.

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Chapter 2

# Structural Topic Modeling of Artificial Intelligence Research in Human Resource Management

**Gizem Dilan Boztaş**[1]

**Abstract**

The widespread adoption of artificial intelligence technologies has led to comprehensive transformations within organizations. One of the most critical areas affected by this transformation is human resources. In this regard, the study examines the publication performance, research topics, and temporal evolution of the literature on artificial intelligence in human resources management. In the study, 1.999 peer-reviewed publications obtained from the Scopus database over the past ten years were analyzed using the structural topic modeling method, which is a topic modeling approach. As a finding of the analysis, 19 topics were identified. Furthermore, the findings reveal that research on artificial intelligence in human resources management has demonstrated an exponential growth trend during the period of 2016–2025. In terms of topic proportions, the most frequently studied themes were identified as "Digital Transformation in Human Resources Management," "Ethical Recruitment," and "Chatbot Applications," while "Knowledge Management," "GenAI in Assesment" and "Talent Acquisition" were represented at comparatively lower levels. The trend analysis further shows that "Ethical Recruitment," "Green Human Resources Management," "Adoption of Innovation," "Digital Transformation in HRM" and "GenAI in Evaluation" have exhibited consistent growth, whereas "Internet of Things," "Agile Team Management," "Decision Support," "Artificial Neural Networks," "Project Management," and "Robotics" have followed a declining trajectory. On the other hand, it was also identified that "Machine Learning," as a fundamental technology, and "Chatbot Applications," as one of the most frequently studied themes, did not display statistically significant trends. Overall, the findings indicate that research on artificial intelligence in human

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resources management has been shifting its focus from purely technical aspects toward dimensions such as ethics, sustainability, and social impacts; however, this transformation has so far taken place only at a limited level.

## 1. INTRODUCTION

The adoption of artificial intelligence (AI) within organizations has reshaped how firms generate and deliver value. In particular, the rapid advancement of machine learning and natural language processing two key branches of AI has strengthened the capacity of enterprises to base their decisions on data, thereby improving efficiency in operations. These developments have accelerated the integration of AI into not only management practices but also diverse organizational units. Among these, human resources management (HRM) stands out as one of the areas most notably influenced by AI-driven solutions.

In recent years, the acceleration of digital transformation has driven the digitalization of HRM processes, reshaping HRM practices by fostering a shift toward innovative, data-driven approaches (Vrontis et al., 2022). Today, AI in HRM plays a crucial role in a wide range of processes, including the use of chatbots in recruitment (Shenbhagavadivu et al., 2024), predictive analytics in candidate evaluation, performance assessment of employees, and the management of training programs (Dima et al., 2024). Furthermore, research suggests that a significant shift in the global workforce due to AI is imminent. For instance, the World Economic Forum projects that by 2030, AI and computing technologies will create 11 million new jobs while eliminating 9 million existing ones. The same report highlights that approximately one-third of tasks will be performed by machines and another one-third through human–machine collaboration (World Economic Forum, 2025). These projections underscore the strategic role of HRM and emphasize the need for a redefinition of HR professionals' roles.

While AI creates opportunities in the HRM context, it also introduces notable challenges. (Palos-Sánchez et al. (2022) examine these opportunities and challenges across three dimensions: employees, enterprises, and society. From the employee perspective, automation of routine tasks by AI presents an opportunity to focus on more analytical and strategic roles (Murphy, 2024). Another key benefit is the acceleration of reskilling processes, as AI supports personalized training programs that enable employees to adapt to the digital era (Gorowara et al., 2024). At the same time, challenges such as job insecurity, techno-stress, ethical concerns, and weakened interpersonal relationships due to human–machine interaction have been widely reported (Ali et al., 2024; Du, 2024; F. Khan & Hagglund, 2025).

From the enterprise perspective, AI offers significant opportunities across a broad spectrum of HRM processes, ranging from recruitment to performance evaluation and talent development, by enhancing efficiency, reducing costs, and supporting data-driven decision-making (Kadirov et al., 2024). However, high integration costs, algorithmic biases, data privacy issues, and gaps in ethical governance represent important risks for enterprises (Du, 2024). At the societal level, the use of AI in HRM is reshaping employment structures, creating new job categories, and fostering more inclusive workforce models. Nevertheless, it also brings serious risks such as the deepening of the digital divide and increased unemployment (Bircan & Özbilgin, 2025). Consequently, the sustainability and ethical deployment of AI in HRM depend on balanced strategies that require collaboration among employees, enterprises, and society.

The use of AI tools in HRM has enhanced processes, making them more streamlined and effective, and has created a strong momentum toward shaping the future of this field. This trend has also elevated the academic relevance of the topic. The expanding research on AI within HRM offers important insights into its influence on organizational practices nevertheless, the fast-growing volume of studies makes it challenging to obtain an overall perspective. This fragmented nature underlines the necessity for a holistic evaluation of the area. Previous research indicates that most works are based on systematic reviews (Madanchian et al., 2023) or bibliometric analyses (Laviola et al., 2024), often based on relatively small samples. While these contributions are valuable, only a few studies have made use of topic modeling to explore the incorporation of AI into HRM.

The purpose of this study is to examine the body of research on AI in HRM from the past ten years by applying the structural topic modeling method, with the goal of uncovering the key research themes and their evolution over time. Consistent with this objective, the following research questions are posed:

**RQ1:** What are the publication performance of research on AI in HRM?

**RQ2:** What are the main research topics of AI in HRM?

**RQ3:** What are the temporal trends of AI in HRM research topics?

## 2. LITERATURE REVIEW

The increasing use of AI technologies in HRM has generated considerable interest in both academic and practical contexts. In line with this trend, literature reviews in the field aim to identify the scope of existing studies, their methodological diversity, and the research gaps. As previously noted, these review studies can generally be categorized into two dimensions: systematic literature reviews and bibliometric analyses.

Within this framework, Gélinas et al. (2022) analyzed 85 studies and, in addition to six classes of the human resources lifecycle, proposed a seventh dimension entitled "Legal and Ethical Issues." Similarly, Jatobá et al. (2023) reviewed 61 articles and demonstrated that the AI–HRM literature clusters into four thematic groups: "Strategic HR and Artificial Intelligence," "Recruitment and Artificial Intelligence," "Training and Artificial Intelligence," and "The Future of Work." Tuffaha (2023), in a review of 34 studies, revealed that biased AI applications could negatively influence core HRM functions such as recruitment, performance management, compensation, and training. In another study, Dima et al. ( 2024) examined 43 investigations into AI in HRM and highlighted the opportunities and challenges in this field. Finally, Bujold et al. (2024) evaluated 107 articles and noted that most studies focused primarily on technical aspects, while principles of responsible AI—such as bias, transparency, and ethics—were insufficiently addressed.

Similar findings were also reported in bibliometric analyses. For example, Palos-Sánchez et al. (2022) examined 73 studies in the context of AI in HRM using bibliometric methods and found that most research focused on recruitment and selection processes, while other HRM subfields were relatively neglected. Mathushan et al. (2023), analyzing 67 articles, demonstrated that the HRM-AI field represents a continuously evolving research domain and identified ten clusters ranging from multi-agent systems to human–robot interaction. Kaushal et al. (2023), through the evaluation of 344 studies, reported that AI has been particularly integrated into fundamental HRM functions such as recruitment, selection, orientation, training, and performance analysis, while also playing a central role in talent acquisition, management, and retention. Supporting these findings, Arora et al. (2024), in their study of 1,414 articles, identified a growing interest in the application of diverse AI techniques in HRM, thereby confirming the field's increasing relevance. More recently, Benabou and Touhami (2025), through a systematic literature review and bibliometric analysis of 77 studies, examined the current state of AI applications in HRM and identified three key themes: the transformative role of AI, human–AI collaboration, and the opportunities and challenges of applications. Similarly, Koştı and Kayadibi, (2025), in their bibliometric analysis of 522 studies, revealed a shift in research focus from technical infrastructure toward more human-centered and ethical dimensions.

In addition to the prevalence of systematic literature reviews and bibliometric analyses, only a limited number of studies have examined AI–HRM research using topic modeling approaches. For instance, Venugopal et al. (2024) applied the BERTopic method to 389 AI–HRM studies. Their findings showed that AI proved beneficial in key HRM activities such as hiring, employee retention, and managing performance, while at the same time drawing attention to ethical challenges like algorithmic bias, protection of personal data, and building employee trust.

As the literature review suggests, existing studies have largely concentrated on identifying the main themes, opportunities, and challenges in HRM-AI. However, most of these works provide general assessments of the field and do not thoroughly address the temporal evolution of research topics. Against this backdrop, the present study aims to analyze the thematic structure and temporal dynamics of AI applications in HRM based on a comprehensive dataset of 1.999 studies, employing the structural topic modeling method. By virtue of its large sample size and the use of a distinct methodology, this study distinguishes itself from prior research and is expected to contribute original insights to the HRM-AI literature by providing a more in-depth understanding of the field.

## 3. METHOD

### 3.1. Structural Topic Modeling (STM)

Topic modeling is a text analysis method that uncovers hidden themes in documents by examining word distributions (Blei, 2012). The STM model, introduced by Roberts et al. (2013), builds on Latent Dirichlet Allocation (LDA), one of the most common techniques in this area. However, unlike LDA, STM incorporates metadata associated with the text (e.g., year, gender, etc.) into the analysis process, thereby overcoming this limitation of LDA (Park et al., 2025; Roberts et al., 2016). Metadata in STM can be used to capture either topic prevalence, topic content, or both. Topic prevalence refers to the extent to which a document is associated with a particular topic, and the inclusion of metadata as a covariate allows topic distribution to vary according to the selected variable. Topic content, on the other hand, refers to the words selected to represent a given topic. Incorporating metadata as a content covariate enables the choice of words within a topic to vary depending on the specific context (e.g., year, gender, platform). These advantages render STM more powerful than traditional topic modeling approaches. In sum, by modeling texts contextually, STM enables deeper analyses compared to classical LDA (Roberts et al., 2019).

### 3.2. Data Collection and Preprocessing

One of the most critical steps in topic modeling studies is the construction of a suitable and reliable dataset. For this purpose, the Scopus database, which is internationally recognized for its high academic credibility, was selected. To construct the dataset, academic publications containing the terms "human resource management" and "artificial intelligence" in their titles, abstracts, or keywords were retrieved from Scopus. After applying the necessary filters, a total of 1,999 peer-reviewed academic studies published in English between 2016 and 2025 were obtained.

Since the quality of data preprocessing directly affects both the performance of the model and the interpretability of the findings, this process was carried out meticulously. Accordingly, a systematic four-step preprocessing procedure was implemented. First, all words in the texts were converted to lowercase. Second, web links, numerical expressions, punctuation marks, and special symbols were removed from the dataset. Third, meaningless English stopwords (e.g., the, and, or, a, an) were eliminated. Finally, lemmatization was performed to reduce words to their meaningful root forms. After completing these steps, the cleaned text data were transformed into numerical form using the bag-of-words approach, and a document-term matrix was constructed on this basis.

### 3.3. Data Analysis

In this research, the STM method was applied to uncover latent topics within the texts. As STM functions as an unsupervised learning model, the precise determination of the topic number (k) plays a crucial role in ensuring valid and reliable outcomes. Choosing an excessively high k may result in overlapping or narrowly specified topics, whereas setting it too low can lead to overly broad and ambiguous topics (Ulstein, 2024). To address this, several trial models were tested with k values ranging between 10 and 40 in order to determine the most suitable number of topics for the dataset.

These models were evaluated based on the metrics of semantic coherence and exclusivity. Semantic coherence measures the extent to which the identified topics are perceived as meaningful by humans, specifically assessing how semantically related the most probable words within a topic are. Exclusivity, on the other hand, evaluates the uniqueness of a topic by examining how frequently its dominant words appear in other topics (Chen et al., 2024). Topics with higher exclusivity scores contain more specific and distinguishable words, thereby facilitating interpretation.

Based on these evaluations, it was determined that the highest semantic coherence and exclusivity scores were obtained when k = 19 (Figure 1). Accordingly, subsequent analyses were conducted using a 19-topic structure. In addition, publication year was incorporated into the model as a metadata covariate. During the interpretation process, both the highest probability words and the FREX words calculated as the weighted average of frequency and exclusivity scores to capture the relative importance of words within topics were considered. On the basis of these two measures, meaningful and representative labels were assigned to each topic.

Finally, the temporal trends of the identified topics were determined using the Mann–Kendall statistical test. All analyses were conducted in the RStudio environment using the "stm" package.

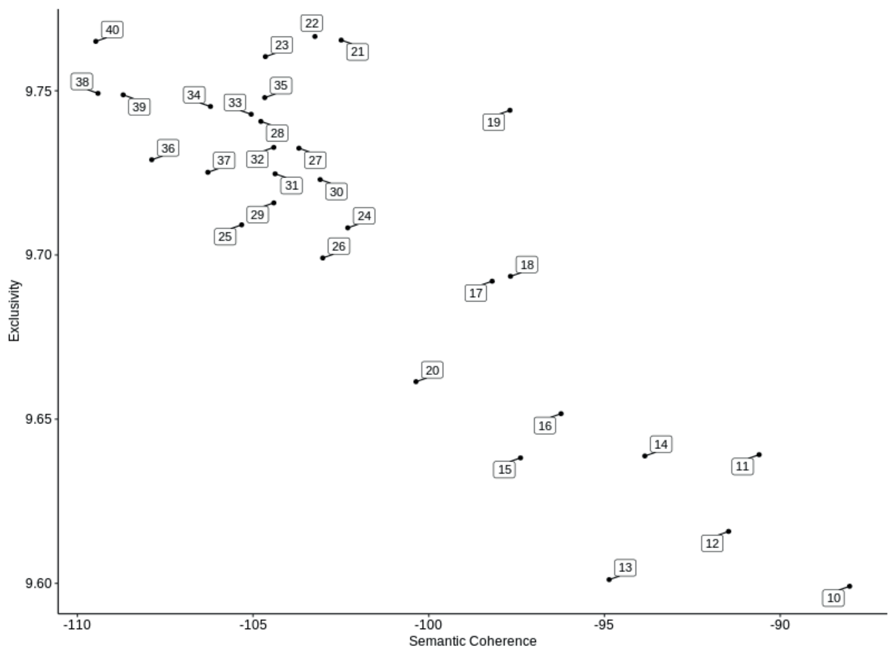


*Figure 1. Comparison of semantic coherence and exclusivity scores of topic models*

## 4. RESULTS

### 4.1 Publication Performance (RQ1)

The findings regarding the progression of 1.999 studies on AI in HRM conducted between 2016 and 2025 are presented in Figure 2. The figure shows that research on the use of AI in HRM has exhibited an exponential upward trend over the years. During the 2016–2019 period, the share of publications within the total remained limited, ranging between 2% and 5%. However, starting in 2020, a noticeable acceleration occurred, with this share rising to the range of 7%–11%. In the years 2023–2025, a substantial surge was observed, as the number of publications increased from 328 to 430, accounting for approximately 16%–22% of the total.

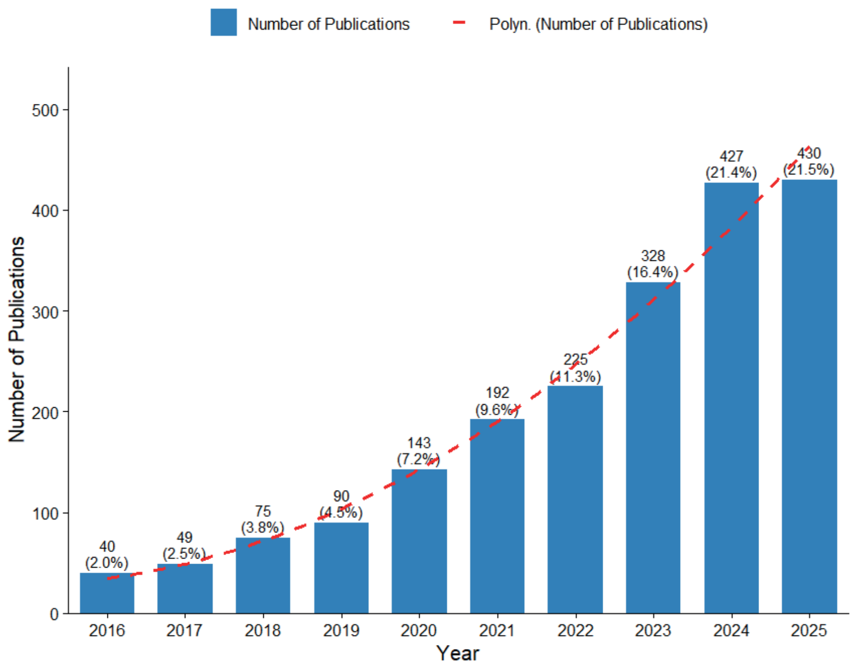


***Figure 2. Yearly Distribution of Publications***

## 4.2. Topic Identification (RQ2)

Table 1 displays the 19 topics derived from the STM analysis, together with the most influential keywords, their relative proportions in the corpus, and the assigned labels. The topics are organized in descending order according to their share within the text. Examination of the table shows that the most prominent theme in the HRM-AI literature is "Digital Transformation in HRM" (6.33%). This is followed by "Ethical Recruitment" (6.23%) and "Chatbot Applications in HRM" (6.00%). Conversely, topics studied at comparatively lower levels include "Knowledge Management in HRM" (3.62%), "GenAI in Evaluation" (2.76%), and "Talent Acquisition" (2.27%).

***Table 1. Labels, Keywords, and Rate for 19 Topics***

| No | Topic Label | Highest Probability Words | FREX | Rate (%) |
|---|---|---|---|---|
| 16 | **Digital Transformation in HRM** | digital, transformation, industry, change, automation, customer, company, sector, machine, smart | digital, transformation, manufacturing, customer, blockchain, revolution, industry, digitalization, product, smart | 6.33 |
| 4 | **Ethical Recruitment** | employee, recruitment, workplace, workforce, bias, retention, concern, selection, impact, efficiency | bias, recruitment, workplace, retention, privacy, fairness, workforce, concern, selection, stress | 6.23 |
| 7 | **Chatbot Applications in HRM** | application, field, function, company, chatbot, tool, opportunity, development, interview, manager | chatbot, marketing, behaviour, function, field, interview, analyse, organisation, managerial, opportunity | 6 |
| 5 | **Intelligent Systems** | enterprise, development, big, intelligent, application, financial, company, analyze, personnel, promote | enterprise, financial, big, accounting, intelligent, internal, reform, mode, forward, modern | 5.91 |
| 1 | **Internet of Things (IoT)** | platform, iot, application, smart, thing, device, sensor, internet, realtime, detection | device, iot, sensor, city, record, thing, computing, detection, platform, camera | 5.73 |
| 14 | **Machine Learning** | machine, learning, employee, accuracy, predict, algorithm, feature, technique, turnover, dataset | turnover, attrition, predict, dataset, accuracy, forest, classifier, machine, nlp, resume | 5.63 |
| 12 | **Occupational Safety** | risk, safety, control, operation, security, worker, maintenance, production, personnel, monitoring | safety, plant, control, risk, accident, maintenance, gas, helmet, security, transportation | 5.6 |
| 9 | **HRM in Tourism** | industry, job, worker, skill, change, people, future, tourism, market, hospitality | tourism, hospitality, job, labor, hotel, employment, industry, worker, disruptive, market | 5.3 |
| 13 | **Project Management** | project, software, manager, development, engineering, stakeholder, framework, tool, quality, skill | project, software, engineering, stakeholder, cycle, phase, lifecycle, product, manager, workshop | 5.12 |

| | | | | |
|---|---|---|---|---|
| 11 | **Neural Network Algorithms** | network, algorithm, neural, propose, scheduling, energy, staff, technique, allocation, support | scheduling, neural, network, energy, consumption, allocation, text, building, minimize, fault | 4.87 |
| 15 | **Innovation Adoption** | adoption, employee, relationship, impact, innovation, examine, investigate, reveal, positive, collect | adoption, positively, relationship, structural, equation, perceive, positive, readiness, rpa, intention | 4.71 |
| 10 | **Training in HRM** | education, training, high, quality, university, algorithm, personnel, efficiency, ability, propose | education, university, training, weight, quality, high, school, ability, calculation, experimental | 4.66 |
| 3 | **Decision Support** | decision, support, recommendation, expert, group, staff, order, people, selection, propose | decision, treatment, recommendation, expert, rank, making, support, fit, fuzzy, preliminary | 4.52 |
| 18 | **Robotics** | task, robot, interaction, trust, algorithm, worker, coordination, team, autonomous, action | robot, autonomous, trust, coordination, task, uncertainty, action, mission, multiagent, coordinate | 4.19 |
| 6 | **Green HRM** | performance, employee, sustainable, green, environmental, behavior, training, impact, development, goal | green, performance, sustainable, ghrm, environmental, appraisal, employee, motivation, behavior, corporate | 3.99 |
| 2 | **Agile Team Management** | team, member, agile, teamwork, change, support, communication, manager, dynamic, performance | agile, member, team, teamwork, humanai, intervention, active, share, cognition, coordination | 3.97 |
| 8 | **Knowledge Management in HRM** | knowledge, service, healthcare, create, company, innovative, support, transfer, solution, customer | knowledge, transfer, service, ict, healthcare, sharing, community, innovative, exchange, cyber | 3.62 |
| 17 | **GenAI in Assement** | assessment, generative, social, tool, chatgpt, genai, task, application, administrative, question | generative, chatgpt, assessment, genai, administrative, gai, prompt, medium, question, feedback | 2.76 |
| 19 | **Talent Acquisition** | talent, firm, acquisition, employer, competitive, skill, advantage, hiring, hire, structure | talent, employer, acquisition, firm, brand, hiring, reputation, hire, competitive, qualified | 2.27 |

### 4.3. Temporal Evolution of Topics (RQ3)

The temporal changes and trends of the 19 topics reflecting research on AI in HRM over the past decade are presented in Figure 3 and Table 2. As shown in Figure 3, the topics "Ethical Recruitment," "Green HRM," "Innovation Adoption," "Digital Transformation in HRM," and "GenAI in Assement" have exhibited a steady increase, becoming more prominent over time. The findings in Table 2 confirm that these upward trends are statistically significant. In contrast, the topics "Internet of Things," "Agile Team Management," "Decision Support," "Knowledge Management in HRM," "Neural Networks," "Project Management," and "Robotics" have displayed a declining trend over the years, and these trends are statistically significant as well. The remaining seven topics—"Intelligent Systems," "Chatbot Applications in HRM," "HRM in Tourism," "Training in HRM," "Occupational Safety," "Machine Learning," and "Talent Acquisition"—did not demonstrate any statistically significant upward or downward trend during the past decade.

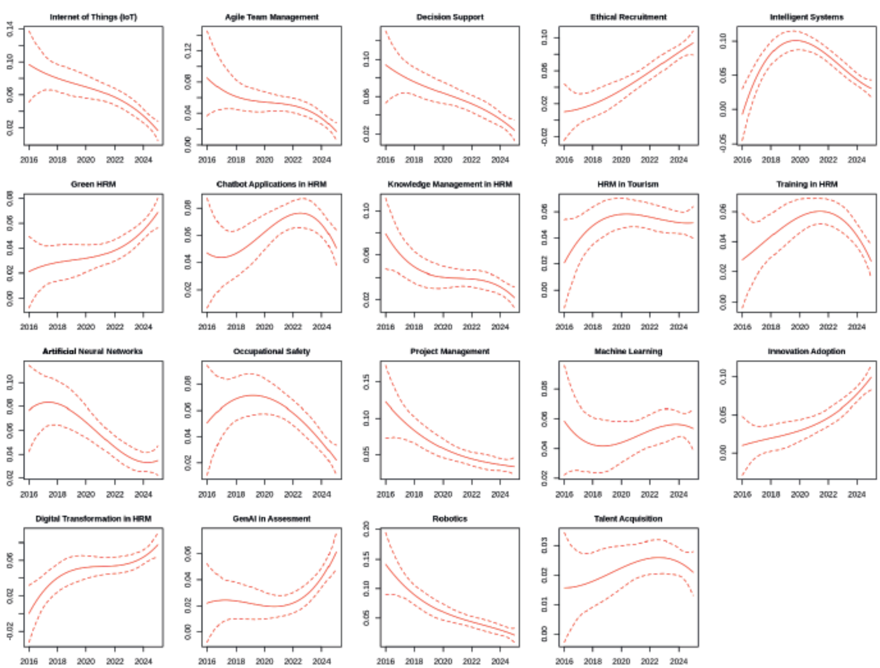


*Figure 3. Temporal Distribution of the 19 Topics*

*Table 2. Trend Analysis of the 19 Topics*

| Topics | S | z | P-value | Direction |
|---|---|---|---|---|
| Internet of Things (IoT) | -35 | -3.041 | 0.00236** | ↓↓↓↓ |
| Agile Team Management | -27 | -2.326 | 0.02* | ↓↓↓↓ |
| Decision Support | -37 | -3.22 | 0.00128** | ↓↓↓↓ |
| Ethical Recruitment | 37 | 3.22 | 0.00128** | ↑↑↑↑ |
| Intelligent Systems | 3 | 0.179 | 0.858 | ↑↑↑↑ |
| Green HRM | 43 | 3.757 | 0.000172*** | ↑↑↑↑ |
| Chatbot Applications in HRM | 19 | 1.61 | 0.107 | ↑↑↑↑ |
| Knowledge Management in HRM | -33 | -2.862 | 0.00421** | ↓↓↓↓ |
| HRM in Tourism | 11 | 0.894 | 0.371 | ↑↑↑↑ |
| Training in HRM | 9 | 0.716 | 0.474 | ↑↑↑↑ |
| Artifical Neural Networks | -31 | -2.683 | 0.00729** | ↓↓↓↓ |
| Occupational Safety | -19 | -1.61 | 0.107 | ↓↓↓↓ |
| Project Management | -35 | -3.041 | 0.00236** | ↓↓↓↓ |
| Machine Learning | 9 | 0.716 | 0.474 | ↑↑↑↑ |
| Innovation Adoption | 39 | 3.399 | 0.000677*** | ↑↑↑↑ |
| Digital Transformation in HRM | 27 | 2.326 | 0.02* | ↑↑↑↑ |
| GenAI in Assement | 23 | 1.968 | 0.0491* | ↑↑↑↑ |
| Robotics | -41 | -3.578 | 0.000347*** | ↓↓↓↓ |
| Talent Acquisition | 7 | 0.537 | 0.592 | ↑↑↑↑ |

***Note:** *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; $p \geq 0.05$. Direction: ↑ indicates increase, ↓ indicates decrease. S and z denote the Mann–Kendall test and the z-test, respectively.*

## 5. DISCUSSION

### 5.1. Publication Performance

Research on AI in HRM demonstrated an overall upward trend during the 2016–2025 period. The acceleration in publication numbers, particularly after 2020, indicates the influence of the pandemic in this field. Moreover, the rapid growth observed from 2023 onwards reflects the increasing popularity of artificial intelligence technologies, especially generative artificial intelligence applications. These findings, consistent with previous studies, reveal that the use of artificial intelligence in HRM has recently emerged as a rapidly growing research domain that is gaining significant attention among scholars (Koştı & Kayadibi, 2025).

### 5.2. Topic Identification

As a finding of the analysis, 19 topics were identified and evaluated according to their proportions within the corpus. Within the scope of this study, the discussion focuses on the three most prominent topics and the three least popular ones.

The findings indicate that the most dominant theme in the HRM-AI literature is "Digital Transformation in HRM" (Table 1). Digital transformation represents one of the core notions of today's era. With its interdisciplinary nature, it extends its impact across a wide range of fields. Owing to its interdisciplinary character, it exerts influence across multiple domains and offers wide-ranging applications based on collaboration across various sectors (Gurcan et al., 2023). Importantly, digital transformation does not solely represent technological change but also entails a comprehensive process that requires organizations to redefine their business practices and reassess their human capital (Qureshi, 2023). Consequently, HR functions occupy a central position in this strategic transformation. The acceleration of digitalization after the pandemic, the rise of flexible working models, and the widespread adoption of artificial intelligence technologies have collectively fostered intensive implementation of digital transformation in core HR areas such as recruitment, performance management, and employee development (Dyakiv et al., 2024). Taken together, these elements explain why digital transformation has emerged as the most salient and up-to-date theme in the HRM-AI literature, consistently attracting scholarly attention. Another key topic that stands out is "Ethical Recruitment", a finding that is consistent with previous studies (Kaushal et al., 2023; Venugopal et al., 2024). In recent years, the ethical dimension has increasingly been addressed across multiple HR subdomains, including recruitment processes (Koştı & Kayadibi, 2025). The prominence of this topic can be attributed to the challenges arising from the integration of AI into recruitment practices. Raghavan et al. (2019) reported that the use of AI in hiring raises concerns regarding bias, fairness, and transparency. Because AI models are trained on past data, they may reproduce biases and lead to unequal treatment based on attributes like gender, age, or ethnicity, which in turn intensifies ethical discussions. In addition, the European Union's AI Act defines AI systems used in recruitment as "high-risk" systems (European Commission, 2024), which further explains the prioritization of this issue by researchers. A third priority topic identified in this study is "Chatbot Applications in HRM." The growing interest in this topic is largely explained by the potential of chatbots to reduce the routine workload of HR professionals. Chatbots can efficiently conduct preliminary interviews, answer frequently asked questions, and carry out initial screening during recruitment, thereby streamlining the process for both candidates and HR specialists (N. Khan & Waseem, 2025). Furthermore, the widespread adoption of remote recruitment practices during the pandemic made chatbots even more visible in HR contexts. Beyond recruitment, chatbots also provide valuable support in training, employee development, and performance management (Sangu et al., 2024). Another notable result of this research is the recognition of underexplored areas within the HRM–AI literature. For instance, "Knowledge Management in HRM" has received comparatively little scholarly attention. This limited emphasis may be due to the fact that AI applications in HRM tend to concentrate more on domains like recruitment, performance evaluation, and employee involvement, where outcomes are considered more applicable and directly useful. Ferreira et al. (2022) emphasize that knowledge management in HRM is more closely associated with indirect, long-term, and organizational-level outcomes, which may account for its marginalization in short-term application-oriented AI research.

The relatively low representation of "GenAI in Assement" may be attributed to the novelty of generative AI technologies and the limited number of existing studies in the literature. Moreover, the persistence of ethical concerns surrounding AI has impeded the widespread adoption of experimental studies in this area, further explaining this finding. Another less prominent topic is "Talent Acquisition." However, this finding contrasts with the study by Kaushal et al. (2023). The discrepancy may be due to differences in the number of publications examined and the time frame covered. It also reflects a shift whereby researchers, in line with technological developments, increasingly study talent acquisition not in isolation but in connection with broader structures such as data-driven approaches, candidate experience, and employer branding. Prikshat et al. (2023) likewise emphasize that most HRM-AI studies concentrate on recruitment, within which the concept of talent acquisition has been reshaped. This suggests that researchers encounter challenges in directly associating talent acquisition with artificial intelligence. As a finding of the analysis, 19 topics were identified and evaluated according to their proportions within the corpus. Within the scope of this study, the discussion focuses on the three most prominent topics and the three least popular ones.

### 5.3. Temporal Trends of Topics

An examination of the findings on the temporal changes of the 19 topics reveals that while some topics exhibit significant upward or downward trends, others display a fluctuating trajectory over the years. For instance, "Digital

Transformation in HRM" and "Ethical Recruitment" demonstrate steady and statistically significant increases, confirming these as leading topics in the field and aligning with our earlier findings. This alignment serves as further evidence of the internal consistency of the study. Moreover, the trend analysis underscores that these two topics are becoming increasingly central in HRM-AI research. Since the reasons for their growth were discussed in detail in the preceding section, they are not repeated here. The trend analysis corroborates and strengthens those earlier findings by situating them within their temporal context.

Another noteworthy finding is the consistent upward trajectory of the topic "GenAI in Assement." The increasing trend of this topic may not only be attributed to the novelty of generative AI technologies but also to their direct impact on critical HRM applications such as recruitment and performance evaluation (Manresa et al., 2024; Nyberg et al., 2025). In addition, "Green HRM" and "Innovation Adoption" are among the other topics that show regular and statistically significant growth. The rise in Green HRM can be explained by organizations' growing need to align with sustainability goals, which increasingly influence not only operational processes but also HRM practices. Supporting this finding, Reddy et al. (2024) emphasized that AI contributes to transforming HR processes into more environmentally friendly systems. The steady increase in Innovation Adoption is closely linked to the acceleration of digital transformation during the COVID-19 pandemic. The pandemic forced organizations to adopt new technologies rapidly to maintain competitive advantage, with HR professionals playing a critical role in supporting employees' adaptation to these technologies (Singh & Pandey, 2024). Consequently, topics related to technological adaptation in HRM have emerged as increasingly strategic research areas.

Conversely, the findings also indicate that topics such as "Internet of Things," "Agile Team Management," "Project Management," and "Robotics" have exhibited a declining trend over the past decade. This decline can be explained by the fact that these topics are typically addressed within broader technology management or operational contexts rather than as specific applications of AI in HRM. For example, Internet of Things and Robotics are often associated with automation in physical processes such as manufacturing or logistics, while Agile Team Management and Project Management are more closely tied to organizational processes. Consequently, scholars focusing specifically on AI applications in HRM appear to treat these topics as secondary (Deepa et al., 2024; Prikshat et al., 2023). Another striking finding is the downward trend observed in "Neural Networks." This reflects a methodological shift in HRM-AI literature, where recent studies have increasingly moved beyond classical neural networks toward advanced architectures such as CNNs, RNNs, and LSTMs (Liu et al., 2023). The declining trend in "Decision Support" can similarly be attributed to the evolution of the concept from early rule-based systems to more mature and sophisticated frameworks—where it is now embedded within contemporary contexts such as digital transformation and algorithmic decision-making in HRM (Csaszar et al., 2024).

Finally, the trend analysis indicates that several topics did not demonstrate statistically significant trajectories. Overall, these topics attracted intermittent scholarly attention, but their development fluctuated over the years without showing a clear upward or downward trend (Figure 3). This fluctuation accounts for the absence of significant long-term patterns. Two notable examples are "Machine Learning"—a backbone of AI—and "Chatbot Applications in HRM," one of the most frequently studied themes in the literature. The absence of a significant trend in Machine Learning can be explained by its role as a fundamental enabling technology, which is rarely examined in isolation but rather integrated into specific HRM subdomains such as recruitment, performance evaluation, and training. By contrast, Chatbot Applications in HRM gained substantial visibility during 2022–2023, particularly throughout the pandemic, due to their ability to facilitate communication, automate repetitive tasks, and provide personalized support. However, the subsequent decline in attention after the pandemic findinged in fluctuating research interest over time, which explains why, despite being one of the most extensively studied topics, it did not exhibit a statistically significant upward trajectory.

## 6. CONCLUSION

This research set out to explore how studies on artificial intelligence in human resources management have evolved in terms of publication performance, thematic focus, and overall trends. To achieve this, articles collected from the Scopus database were systematically reviewed and subjected to analysis. The results demonstrate that the field remains dynamic and is continually developing. The findings indicate that digital transformation occupies a central position in HRM-AI research in terms of topic proportions. Furthermore, when topic proportions and trend analysis are considered together, it becomes evident that ethical issues are increasingly being addressed by researchers, and that GenAI technologies, despite being in their early stage, demonstrate steady growth. The trend analysis also points to the growing importance of sustainability at the organizational level. Moreover, the findings suggest that HRM-AI research is not solely focused on technological tools but is gradually shifting toward addressing the ethical, environmental, and social dimensions of these technologies. In particular, the positive and significant upward trends in Ethical Recruitment and Green HRM highlight that AI applications draw attention not only to efficiency gains but also to their potential for creating more sustainable and responsible workplaces. In addition, findings regarding innovation adoption in organizations indicate that researchers also recognize the importance of the human factor for the successful implementation of AI applications. Overall, this study demonstrates that HRM-AI research is increasingly shifting its focus toward the societal and managerial implications of technology. Nevertheless, as this shift remains limited, future research should place greater emphasis on the ethical, sustainability, and social acceptance dimensions of AI applications in HRM.

As with any study, this research has certain limitations. First, only the Scopus database was used; therefore, future studies could benefit from replicating the analysis with data from multiple databases. In addition, utilizing various topic modeling techniques and contrasting their outcomes may offer a more comprehensive understanding of the field. Nevertheless, despite such limitations, this study is anticipated to provide valuable guidance for both experienced scholars and newcomers to the area.

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Chapter 3

# AI-Driven Optimization Techniques for Meal Delivery: Metropolitan Urban Logistics Approach

**Serkan Özdemir**[1]


**Abstract**

This chapter explores how integrating predictive modeling with route optimization can enhance the performance of urban meal delivery systems. Three routing strategies—Greedy, Vehicle Routing Problem (VRP), and VRP enhanced with LSTM-based predictive rebalancing—were evaluated across varying temporal periods throughout the day. Results show that while VRP reduces delivery durations compared to heuristic routing, the hybrid VRP+LSTM model achieves additional efficiency gains by anticipating spatial–temporal demand fluctuations. These improvements translate into lower delivery times, and greater operational stability. Policy implications emphasize the need for open urban data infrastructures, AI-driven optimization frameworks, and adaptive governance models to support sustainable last-mile logistics. The study demonstrates that hybrid predictive–optimization frameworks can significantly advance intelligent and sustainable urban delivery networks.


## 1. Introduction

Urban life is increasingly characterized by speed, convenience, and digital connectivity, with meal delivery emerging as a critical component of this transformation. However, managing efficient delivery operations in densely populated metropolitan areas presents significant challenges. Traffic congestion, fluctuating demand patterns, and intricate urban layouts often strain traditional logistics systems, leading to delayed deliveries, elevated operational costs, and heightened environmental impacts.

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In response, artificial intelligence (AI) has emerged as a transformative tool for urban logistics. By leveraging machine learning algorithms and predictive analytics, AI enables real-time, adaptive decision-making that can optimize delivery routes, forecast demand, allocate courier workloads efficiently, and mitigate emissions (Wang et al., 2023). These techniques shift meal delivery from a reactive to a proactive, data-driven process, capable of navigating complex urban environments with both efficiency and sustainability.

This chapter examines AI-driven optimization strategies for metropolitan meal delivery, emphasizing approaches that integrate urban dynamics, fleet management, and operational efficiency. Its originality lies in the integration of the Vehicle Routing Problem (VRP) framework with Long Short-Term Memory (LSTM)-based demand forecasting to analyze the impact of dynamic courier rebalancing on delivery efficiency. Unlike earlier studies that treated routing and forecasting separately, this chapter presents a unified model linking predictive demand analysis with real-time operational optimization. By analyzing how AI can reduce delays and improve resource allocation, the study provides practical insights for enhancing delivery performance in high-density cities. This work also offers a forward-looking perspective on the digital evolution of urban food delivery, highlighting the potential for AI to create smarter, faster, and more sustainable urban logistics systems.

The chapter is organized as follows: the next section reviews the literature on VRP and AI applications in urban logistics and food delivery; the methodology section presents the case study and introduces the VRP–LSTM integration and rebalancing framework; results and analyses are then presented; and finally, the discussion and conclusion reflect on implications for sustainable urban logistics and future research directions.

## 2. Literature Review

The rapid growth of urban populations, combined with the rising demand for on-demand services, has profoundly transformed the landscape of urban logistics. Among these services, meal delivery platforms have become a cornerstone of modern urban economies, offering convenience to consumers but also introducing new logistical challenges. The dense and dynamic nature of cities creates unique constraints—ranging from traffic congestion and variable demand patterns to narrow delivery windows—that traditional logistics frameworks often fail to address effectively (Savelsbergh & Van Woensel, 2016; Allen et al., 2018). Consequently, there is a growing need for intelligent, adaptive systems that can manage these complexities efficiently. In this context, Artificial Intelligence (AI) has emerged as a transformative enabler, allowing the development of data-driven and self-learning logistics systems that optimize urban delivery operations (Goodchild & Toy, 2018).

A core challenge in meal delivery logistics lies in the optimization of delivery routes, commonly framed as the Vehicle Routing Problem (VRP). The VRP involves determining optimal routes for a fleet of vehicles to service a set of customers while respecting constraints such as delivery time windows, vehicle capacity, and service requirements (Toth & Vigo, 2014). In the specific case of meal delivery, these constraints are even more stringent due to the perishability of food and the high time sensitivity of customer expectations. Over the years, traditional VRP models have evolved into dynamic and time-dependent variants that incorporate real-time traffic data, stochastic travel times, and fluctuating customer demands (Psaraftis et al., 2016). More recently, AI and machine learning (ML) approaches have further advanced VRP solutions by enabling systems to predict and adapt to dynamic urban conditions. Reinforcement learning, deep neural networks, and hybrid optimization models have been applied to achieve faster, more responsive routing decisions (Nazari et al., 2018; Kool et al., 2019).

Equally crucial to efficient meal delivery is demand forecasting, which directly affects how resources are allocated and scheduled. Accurate prediction of customer demand enables platforms to plan for peak hours, allocate riders strategically, and minimize both idle time and delayed deliveries. AI-driven forecasting models leverage diverse data sources, including historical orders, customer profiles, weather conditions, and local events, to forecast demand at fine spatial and temporal resolutions. Machine learning techniques—such as regression models, ensemble methods, and neural networks like LSTMs and CNNs—have demonstrated superior performance in capturing non-linear relationships in demand data (Bandara et al., 2020). Integrating these forecasting models with routing algorithms creates a closed-loop decision system, where anticipated demand informs vehicle routing and resource distribution in real time.

Another essential component of adaptive logistics systems is rebalancing, which refers to the dynamic repositioning of couriers or delivery vehicles in response to fluctuating demand. Without effective rebalancing, meal delivery platforms face inefficiencies such as excessive idle time, underutilized capacity, and unbalanced workloads across the fleet. These AI-driven approaches continuously monitor real-time information—such as order density, traffic flow, and rider availability—to make autonomous relocation decisions, thereby improving service reliability and reducing operational costs. By integrating rebalancing into the overall optimization framework, platforms can achieve smoother demand–supply alignment and enhanced customer satisfaction.

The integration of AI-driven optimization techniques across demand prediction, vehicle routing, and rebalancing creates the foundation for a cohesive, adaptive, and sustainable urban delivery system. Such integration allows real-time decision-making that jointly optimizes routing efficiency, resource allocation, and environmental sustainability. Moreover, the inherent adaptability of AI systems enables rapid responses to disruptions such as traffic incidents or sudden spikes in demand, maintaining high service levels and customer satisfaction even under uncertainty.

Building on this background, the present study explores AI-driven optimization for metropolitan meal delivery systems by integrating demand forecasting, vehicle routing, and rebalancing strategies into a unified system. Specifically, it examines whether cluster-level demand predictions generated by LSTM networks can improve delivery performance by pre-positioning couriers in high-demand zones before orders occur. This approach is compared against conventional greedy routing and standard VRP-based optimization. The study evaluates multiple operational metrics—including average delivery time, congestion impact, and fleet utilization—across various time slots. By combining predictive analytics with dynamic routing and proactive rebalancing, this research aims to demonstrate how AI can effectively reduce service delays, balance workloads, and improve overall system efficiency in complex metropolitan environments. Ultimately, it contributes to the development of a data-driven, adaptive, and sustainable framework for urban meal delivery logistics, illustrating the potential of AI to transform last-mile delivery into a smarter and greener system.

## 3. Methodology

The study focuses on a metropolitan meal delivery scenario inspired by the city of Amsterdam. A synthetic dataset of 1,000 delivery requests was generated, distributed across three representative urban clusters with varying spatial densities. Requests were assigned to 24 hourly time slots, reflecting realistic daily demand patterns, including lunch (10:00–13:00) and dinner (16:00–19:00) peaks (Figure 1). In this study, it is also assumed the riders can carry at most 10 packages in one ride.

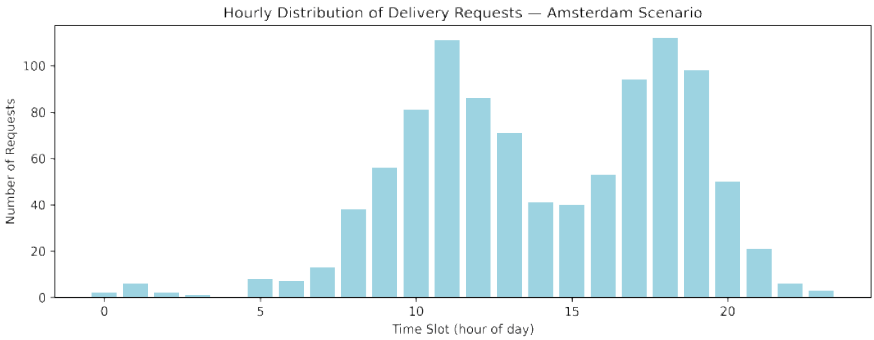


***Figure 1. Temporal Distribution of Delivery Requests***

Geographic coordinates were mapped onto the underlying street network using OSMnx and NetworkX, allowing shortest-path distance computations for all delivery locations and the central depot (Figure 2). This setup enables the simulation of delivery operations in a realistic urban environment, incorporating spatial clustering, demand variability, and network topology constraints.

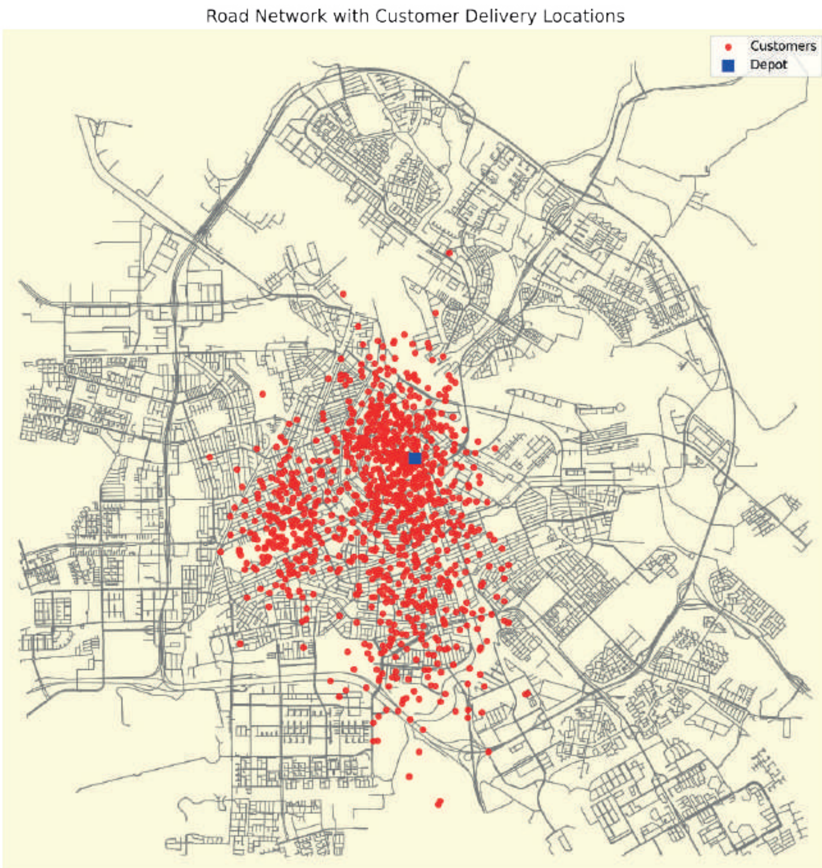


***Figure 2. Road Network of Amsterdam Map with Customer Delivery Locations***

At the first level, a greedy myopic routing algorithm was implemented as a baseline. In this approach, vehicles iteratively serve the nearest feasible request until their capacity constraints are reached, after which they return to the depot. While this method is computationally simple and fast, it does not incorporate global optimization, forecasted demand, or proactive resource allocation, making it a representative benchmark for reactive delivery strategies.

Building on this baseline, the study employs the Capacitated Vehicle Routing Problem (CVRP) framework, implemented using Google OR-Tools, to optimize delivery routes. In this framework, each vehicle departs from the depot, respects capacity constraints, and seeks to minimize total travel distance. Shortest-path distances derived from the street network are used as cost metrics. Solutions are obtained through a combination of pathcheapest-arc first solution strategies and guided local search metaheuristics. Compared to the greedy baseline, this approach provides a globally optimized routing strategy, accounting for spatial clustering of requests and balanced load distribution across vehicles.

To anticipate future delivery demand, a cluster-level LSTM model was trained on historical request patterns. The model predicts demand for each urban cluster in the next time slot using a sliding window of previous hourly demands. These predictions inform pre-positioning strategies, allowing vehicles to be proactively allocated to anticipated “hotspot” clusters. The LSTM is trained on normalized cluster-level demand series, using mean squared error as the loss function, and is updated continuously over the 24-hour simulation horizon.

Rebalancing leverages these LSTM forecasts by allocating a fraction of vehicles to predicted high-demand clusters before each time slot begins. Vehicles assigned to rebalance nodes are incorporated into the VRP as starting points with zero demand, allowing the optimization to simultaneously consider both pre-positioned and depot-based vehicles. This proactive strategy enhances fleet management, reduces service delays, and mitigates congestion during peak periods.

Delivery performance is evaluated by calculating average delivery times per request across 24 time slots. Three strategies are compared: (i) greedy myopic routing, (ii) VRP without rebalancing, and (iii) VRP with LSTM-based rebalancing. Congestion effects are approximated based on the load ratios observed in each time slot, providing insights into the effectiveness of proactive versus reactive routing strategies.

## 4. Results

Table 1 summarizes the average delivery durations obtained from three optimization strategies—Greedy routing, VRP (Vehicle Routing Problem), and VRP with LSTM-based Rebalancing—across 24 hourly time slots. During low-demand periods (Time Slots 0–3 and 21–23), all methods exhibit similar performance due to limited routing complexity. Notably, in Slot 23, the VRP+LSTM approach reduces delivery time from 20.38 minutes (VRP and Greedy) to 16.06 minutes, illustrating the model’s ability to anticipate and adapt to spatial–temporal demand fluctuations.

***Table 1. Performance Comparison of Delivery Durations Across Optimization Strategies***

| Time Slot | Requests | Avg Time Greedy (min) | Avg Time VRP (min) | Avg Time VRP+LSTM Rebalancing (min) |
|---|---|---|---|---|
| 0 | 2 | 27.34 | 25.61 | 25.27 |
| 1 | 6 | 12.29 | 11.45 | 11.45 |
| 2 | 2 | 24.99 | 24.99 | 25.01 |
| 3 | 1 | 25.11 | 25.11 | 25.11 |
| 4 | 0 | 0.00 | 0.00 | 0.00 |
| 5 | 8 | 9.88 | 8.47 | 8.47 |
| 6 | 7 | 11.20 | 10.17 | 10.17 |
| 7 | 13 | 13.61 | 11.39 | 11.22 |
| 8 | 38 | 7.78 | 6.76 | 6.65 |
| 9 | 56 | 7.21 | 6.53 | 6.48 |
| 10 | 81 | 7.40 | 5.75 | 5.80 |
| 11 | 111 | 7.13 | 6.10 | 6.06 |
| 12 | 86 | 7.12 | 6.15 | 6.07 |
| 13 | 71 | 6.64 | 5.60 | 5.47 |
| 14 | 41 | 8.01 | 6.26 | 6.11 |
| 15 | 40 | 8.99 | 7.86 | 7.81 |
| 16 | 53 | 9.23 | 7.30 | 7.31 |
| 17 | 94 | 7.11 | 6.13 | 6.19 |
| 18 | 112 | 7.12 | 5.97 | 5.99 |
| 19 | 98 | 7.27 | 6.03 | 6.11 |
| 20 | 50 | 7.80 | 6.41 | 5.68 |
| 21 | 21 | 12.12 | 8.47 | 7.33 |
| 22 | 6 | 10.23 | 8.38 | 8.38 |
| 23 | 3 | 20.38 | 20.38 | 16.06 |

During medium- to high-demand periods (Slots 8–19), the Greedy algorithm consistently yields longer delivery times, highlighting its suboptimal performance under dense request conditions. The VRP approach achieves up to a 15% reduction in delivery duration relative to the Greedy method, demonstrating the effectiveness of global route optimization. The VRP+LSTM Rebalancing model further enhances performance, providing marginal but consistent improvements across most active time slots. Overall, these results indicate that integrating LSTM-based demand forecasting with VRP improves delivery efficiency and system stability, combining spatial optimization with temporal prediction for the most balanced and robust performance among the evaluated strategies.

Table 2 further quantifies the relative improvements achieved by the VRP and VRP+LSTM Rebalancing models compared to the Greedy baseline. The "VRP vs Greedy (%)" column reflects the percentage reduction in delivery duration achieved by the VRP method, while the "Rebalancing vs VRP (%)" column indicates the additional effect of the LSTM-based rebalancing mechanism. Across most active hours (Slots 5–20), the VRP model consistently outperforms the Greedy algorithm, with reductions ranging from 6% to 22%. The most pronounced improvement occurs at Slot 21, with a 30.12% reduction, demonstrating VRP's robustness under variable and late-hour demand conditions. In contrast, performance differences during low-demand periods remain minimal, reflecting the limited impact of routing optimization when demand is sparse.

*Table 2. Comparative Performance Gains of Optimization Strategies*

| Time Slot | Requests | Avg Time Greedy (min) | Avg Time VRP (min) | Avg Time VRP+LSTM Rebalancing (min) | VRP vs Greedy (%) | Rebalancing vs VRP (%) |
|---|---|---|---|---|---|---|
| 0 | 2 | 27.34 | 25.61 | 25.27 | 6.33 | 1.33 |
| 1 | 6 | 12.29 | 11.45 | 11.45 | 6.83 | 0.00 |
| 2 | 2 | 24.99 | 24.99 | 25.01 | 0.00 | -0.08 |
| 3 | 1 | 25.11 | 25.11 | 25.11 | 0.00 | 0.00 |
| 4 | 0 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 5 | 8 | 9.88 | 8.47 | 8.47 | 14.27 | 0.00 |
| 6 | 7 | 11.20 | 10.17 | 10.17 | 9.20 | 0.00 |
| 7 | 13 | 13.61 | 11.39 | 11.22 | 16.31 | 1.49 |
| 8 | 38 | 7.78 | 6.76 | 6.65 | 13.11 | 1.63 |
| 9 | 56 | 7.21 | 6.53 | 6.48 | 9.43 | 0.77 |
| 10 | 81 | 7.40 | 5.75 | 5.80 | 22.30 | -0.87 |
| 11 | 111 | 7.13 | 6.10 | 6.06 | 14.45 | 0.66 |
| 12 | 86 | 7.12 | 6.15 | 6.07 | 13.62 | 1.30 |
| 13 | 71 | 6.64 | 5.60 | 5.47 | 15.66 | 2.32 |
| 14 | 41 | 8.01 | 6.26 | 6.11 | 21.85 | 2.40 |
| 15 | 40 | 8.99 | 7.86 | 7.81 | 12.57 | 0.64 |
| 16 | 53 | 9.23 | 7.30 | 7.31 | 20.91 | -0.14 |
| 17 | 94 | 7.11 | 6.13 | 6.19 | 13.78 | -0.98 |
| 18 | 112 | 7.12 | 5.97 | 5.99 | 16.15 | -0.34 |
| 19 | 98 | 7.27 | 6.03 | 6.11 | 17.06 | -1.33 |
| 20 | 50 | 7.80 | 6.41 | 5.68 | 17.82 | 11.39 |
| 21 | 21 | 12.12 | 8.47 | 7.33 | 30.12 | 13.46 |
| 22 | 6 | 10.23 | 8.38 | 8.38 | 18.08 | 0.00 |
| 23 | 3 | 20.38 | 20.38 | 16.06 | 0.00 | 21.2 |

The LSTM-based rebalancing mechanism contributes additional improvements over the VRP baseline in several key intervals, including Slots 7–15, 20–21, and 23, with the largest enhancement reaching 21.2% at Slot

23. This indicates that predictive rebalancing effectively anticipates demand imbalances and reallocates couriers to maintain efficient service, particularly during transition or off-peak periods. Negative values observed in Slots 10 and 16–19 suggest minor over-adjustments by the predictive model, likely due to discrepancies between forecasted and actual demand. However, these fluctuations are small (below 1.5%) and do not compromise overall system efficiency. Collectively, these results confirm that combining LSTM-based predictive rebalancing with VRP enhances delivery stability and efficiency across varying demand levels.

Figure 3 illustrates the temporal variation of average delivery durations and relative improvements for the three strategies, highlighting lunch (10:00–13:00) and dinner (16:00–19:00) peak periods. The Greedy algorithm consistently produces longer delivery times, particularly during peaks, whereas the VRP method maintains lower and more stable durations throughout the day. The addition of LSTM-based rebalancing further refines performance, particularly during transitional periods such as early afternoon and late evening, by preemptively redistributing couriers based on predicted demand.

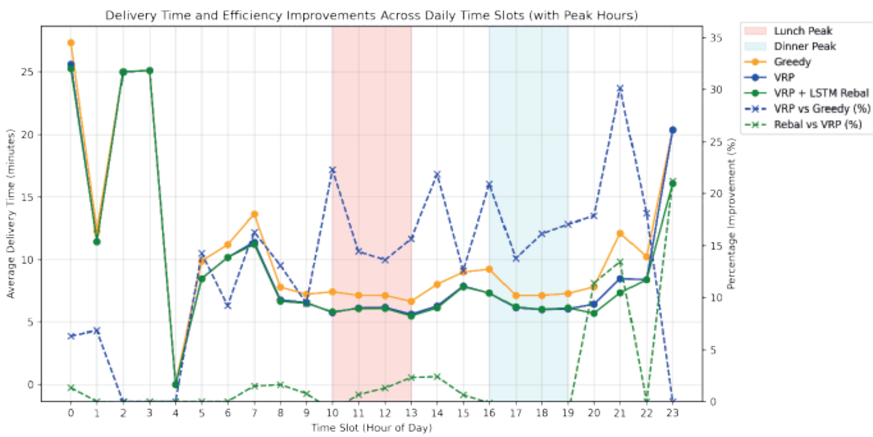


*Figure 3. Temporal Comparison of Delivery Duration and Relative Performance Across Routing Strategies*

The relative improvement curves reinforce these observations. The VRP vs Greedy curve shows consistent gains of 10–25% during peak hours, demonstrating the efficiency advantage of route optimization under dense demand. The Rebalancing vs VRP curve exhibits frequent positive contributions, with localized improvements exceeding 10% in off-peak hours (21:00–23:00), where predictive rebalancing effectively reduces courier idle time. Overall, the figure highlights that the VRP+LSTM Rebalancing strategy delivers the most balanced and resilient performance across daily operational cycles.

Figure 4 depicts average delivery durations overlaid with hourly request volumes, providing a visual link between demand intensity and algorithmic performance. The Greedy method shows high delivery times during periods of elevated demand, emphasizing its limited scalability. The VRP approach demonstrates lower and more stable durations, confirming its system-level routing efficiency. VRP+LSTM Rebalancing further improves performance during high-demand intervals (approximately 10:00–19:00) by dynamically reallocating couriers according to short-term forecasts, thereby maintaining service efficiency under rapidly shifting demand patterns. During off-peak hours, all strategies converge, reflecting minimal optimization impact when demand is sparse.

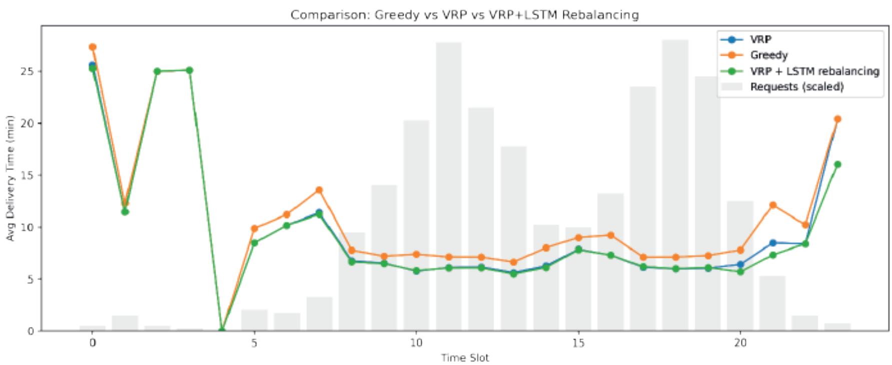


*Figure 4. Temporal Comparison of Delivery Duration and Request Volume*

Finally, Figure 5 presents a comparative visualization of average delivery durations for all three methods across 24 hourly time slots. The Greedy algorithm consistently shows the highest durations, particularly during peak demand, while the VRP-based approach achieves shorter and more stable times throughout the day. The VRP+LSTM Rebalancing model enhances efficiency further, particularly during midday and evening peaks, with the most substantial reductions (up to 20%) observed in late hours (21:00–23:00). These results demonstrate that integrating predictive demand modeling with route optimization yields a more adaptive, resilient, and time-efficient delivery process, highlighting the hybrid method's applicability for urban micro-delivery systems characterized by dynamic and temporally heterogeneous demand.


***Figure 5. Performance Comparison per Time Slot***

## 5. Discussion

The comparative analysis of the three routing strategies—Greedy, VRP, and VRP combined with LSTM-based Rebalancing—reveals distinct operational advantages and limitations across varying demand intensities. Consistent with expectations, the Greedy approach performs adequately under sparse request conditions but exhibits significant inefficiencies as demand density increases. This outcome reflects the algorithm's local optimization behavior, which lacks the capacity to account for global spatial relationships and temporal fluctuations in delivery requests (Savelsbergh & Van Woensel, 2016). In contrast, the VRP method demonstrates a clear performance advantage, achieving substantial reductions in delivery durations during medium to high-demand periods. This improvement underscores the importance of global optimization in coordinating courier assignments and route sequencing, especially within dense urban environments where real-time spatial efficiency is critical (Toth & Vigo, 2014).

The integration of LSTM-based predictive rebalancing into the VRP framework further enhances overall system robustness and adaptability. The hybrid VRP+LSTM approach consistently outperforms the baseline methods, particularly during transitional and off-peak periods, by proactively repositioning couriers based on anticipated demand shifts. This result highlights the potential of combining data-driven forecasting with optimization algorithms to achieve spatio-temporal equilibrium in dynamic delivery systems. The observed improvement of up to 21.2% in certain time slots illustrates that predictive intelligence can effectively mitigate temporal mismatches between supply and demand, reducing idle time and improving service continuity.

Nevertheless, the minor negative improvements observed in a few intervals suggest that predictive rebalancing is sensitive to forecast accuracy. Small deviations between predicted and actual demand can lead to over-adjustments in courier distribution, especially when temporal variability is high. These findings point to a key challenge in predictive optimization which is achieving reliable real-time demand estimation under stochastic and rapidly evolving urban conditions (Goodfellow et al., 2016). Despite these fluctuations, the overall gains in efficiency demonstrate that incorporating LSTM-based demand anticipation enhances delivery system resilience without introducing instability or excessive computational cost.

From a broader perspective, these results emphasize the strategic value of integrating machine learning with classical optimization in urban logistics. The VRP+LSTM framework not only improves operational performance but also aligns with sustainability goals by reducing redundant travel and optimizing resource utilization (Klumpp, 2021). Shorter and more stable delivery times translate to reduced energy consumption, fewer emissions, and improved customer satisfaction. These factors are increasingly critical in the design of sustainable meal delivery systems. Moreover, the system's adaptability during both peak and off-peak hours reflects a capacity for continuous performance balancing, an essential feature for modern on-demand platforms operating under volatile demand conditions (Savelsbergh & Van Woensel, 2016).

Therefore, the findings validate that a hybrid predictive–optimization approach offers a superior balance between efficiency and robustness compared to purely heuristic or static optimization methods. By anticipating demand trends and integrating them into routing decisions, urban delivery systems can achieve more intelligent resource deployment, enhanced temporal stability, and greater responsiveness to consumer needs. These insights contribute to the ongoing discourse on sustainable and adaptive logistics systems, underscoring the transformative role of AI-driven predictive modeling in the evolution of urban mobility and last-mile delivery operations (Cattaruzza et al., 2017; Ghiani et al., 2022).

The findings of this study carry several important implications for policymakers, urban mobility planners, and researchers aiming to develop more efficient and sustainable last-mile meal delivery systems.

The demonstrated efficiency gains from integrating predictive demand modeling into routing operations suggest that public authorities should actively promote the adoption of intelligent logistics systems. This can be achieved through well-designed incentives and regulatory frameworks that facilitate data sharing and encourage the use of AI-driven optimization tools (European Commission, 2020; McKinnon, 2021). Establishing open urban data infrastructures, such as platforms providing real-time information on traffic flow and delivery demand, would further enhance coordination between private operators and municipal authorities, hence reducing congestion and environmental impact (Taniguchi & Thompson, 2014).

The observed improvements in delivery stability and reduced courier idle times also highlight opportunities to better align meal delivery logistics with broader sustainability and decarbonization goals. Cities committed to promoting low-emission transportation can leverage predictive routing technologies to optimize the use of bicycle couriers and other eco-friendly modes, ensuring efficient service delivery without expanding vehicle fleets. Integrating these intelligent routing mechanisms into municipal logistics zones or urban consolidation centers could support more equitable, energy-efficient, and resilient delivery networks that contribute to long-term climate and mobility objectives.

Furthermore, the robustness of the hybrid VRP+LSTM framework across varying demand levels offers valuable insights for designing adaptive urban logistics policies. This adaptability is especially relevant for cities experiencing dynamic retail and e-commerce demand cycles, where conventional static routing regulations often fall short. Embedding predictive analytics into smart-city governance frameworks can therefore enhance strategic decision-making in areas such as transport planning and dynamic pricing for delivery operations (European Commission, 2021). By aligning predictive intelligence with policy innovation, municipalities can create more responsive and sustainable delivery systems capable of adapting to fluctuating urban conditions.

Despite the demonstrated potential of the hybrid VRP+LSTM model, several avenues remain open for future research and practical development. One key direction involves integrating richer, real-time data streams—such as live courier positions, weather conditions, and traffic dynamics—to further enhance predictive accuracy and adaptability. Strengthening collaboration between urban authorities, logistics providers, and technology developers will also be essential for implementing and testing these predictive routing systems in real-world environments. Such pilot projects can provide valuable empirical insights into operational feasibility, human–AI coordination, and data governance challenges, bridging the gap between simulation and deployment.

Beyond the technical and operational dimensions, future investigations should also address the social and ethical implications of predictive logistics. Ensuring fairness in task allocation, transparency in algorithmic decision-making, and protection of courier autonomy will be vital for building equitable and trustworthy AI-driven delivery systems. Addressing these aspects will not only strengthen public acceptance but also ensure that technological innovation supports the overarching goals of sustainable, inclusive, and human-centered urban development.

## 6. Conclusion

In conclusion, the integration of LSTM-based predictive rebalancing with VRP optimization represents a promising pathway toward sustainable, adaptive, and intelligent urban delivery systems. By combining spatial optimization with temporal foresight, cities and logistics operators can achieve greater efficiency, lower environmental impact, and improved service reliability which are key pillars for advancing sustainable urban logistics in the age of digitization.

In addition, this research makes a distinctive contribution to the existing body of knowledge by establishing a comprehensive model that synthesizes temporal demand forecasting with spatial route optimization, hence illustrating how data-driven predictive mechanisms can substantially enhance the efficiency, responsiveness, and resilience of meal delivery logistics operations.

The case study analysis demonstrates substantial performance gains over greedy and conventional VRP approaches, particularly in terms of delivery duration. Notably, the implementation of predictive rebalancing resulted in an average 2.29% decrease in average delivery duration comparing traditional VRP approach, thereby providing quantitative evidence of the model's operational efficacy and scalability in dynamic urban contexts.

From a policy perspective, these findings emphasize the importance of integrating predictive analytics into urban logistics governance. Policymakers should promote the adoption of intelligent logistics systems through incentives and regulatory frameworks that support data sharing and AI-based optimization. Developing open urban data infrastructures and providing real-time information on traffic, and delivery demand can further strengthen coordination between municipalities and private operators while advancing sustainability and decarbonization goals through greater use of low-emission transport modes.

Future research should extend this study by incorporating richer real-time data sources, such as courier locations, weather, and traffic dynamics, to improve predictive accuracy and adaptability. Collaborative pilot projects between city authorities, logistics providers, and technology developers are essential to assess real-world feasibility and governance challenges. Furthermore, addressing ethical concerns such as fairness in task allocation, transparency in algorithmic decisions, and courier autonomy will be crucial for ensuring that AI-driven delivery systems remain inclusive, equitable, and aligned with the broader goals of sustainable urban development. Lastly, by integrating spatial optimization with temporal foresight, this study presents a pathway toward efficient, low-impact, and reliable delivery solutions which are key areas of sustainable urban logistics in the digital age.

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Chapter 4

# A Decision Support System Approach for Early Diagnosis of Digital Addiction Observed in Generation Z

**Yasin Kırelli** [1]

**Abstract**

This study presents a decision support system for the early diagnosis of digital addiction observed in Generation Z individuals. Born in the digital age, Generation Z actively uses the internet and social media as a means of social interaction, which leads to digital addiction. At this stage, when identity formation has just begun, digital addiction causes negative consequences such as social isolation, academic failure, anxiety, and depression. The aim of the study is to model the levels of digital addiction using machine learning methods by observing the effects of smartphone usage habits among students aged 12 to 21 in this context. This model has been created by observing daily phone usage statistics. The publicly available data set used in the study has been collected through structured surveys. The dataset shows that screen time is 4.5 hours across all age groups. A relationship between screen time exceeding eight hours and addiction has also been observed. Four different classification algorithms (Logistic Regression, Gradient Boosting, Neural Net (MLP), XGBoost) have been used in the study. Among the models, the Logistic Regression model showed the highest accuracy in classification performance. Compared to similar studies in literature, the machine learning approach has higher prediction success in classifying the level of digital addiction. This study, which applies a data-driven analytical approach to the problem of digital addiction in early ages when identity formation is just beginning, emphasizes the significance of developing early diagnosis and intervention strategies.

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## 1. Introduction

Information and communication technologies play an integral role in our daily lives in this digital age. Individuals born after 1995 are referred to as Generation Z. Social media platforms provided by the internet infrastructure play a significant role in their identity formation process (Li et al., 2023; Ricoy et al., 2022). This is because they use these platforms for social interaction. The internet is not only used as a means of communication by this generation, but it is also considered a fundamental part of life, including social interaction, education, and entertainment (Akhtar et al., 2023; Herawati et al., 2022; Li et al., 2023). The development of communication and internet technology has enabled instant connectivity and artificial intelligence technologies to provide personalized and rich content tailored to the user, making life easier and faster. The pursuit of social approval in digital spaces often results in unregulated use, excessive content consumption, and digital dependency. Negative effects on social relationships, academic life, and work life have also been experienced because of this situation (Hamida et al., 2021; Huang, 2024; Jun, 2015).

Digital addiction arises when individuals are unable to control their use of technological devices, which can lead to adverse results like social isolation, poor physical health, and diminished mental well-being. The emergence of negative emotional states, such as restlessness and anxiety, is associated with the absence of individuals from technological devices or the internet. People define digital addiction not only as high screen time but also as a type of psychological addiction. This psychological condition, known as nomophobia, is characterized in literature as the state of being without a smartphone. There are important factors in the emergence of this psychological problem in Generation Z, and it is essential to understand these factors to develop effective solutions. The existence of factors such as competence, belonging, feelings of loneliness, and the search for excitement can serve as triggers for digital addiction. Additionally, family and friends' attitudes towards young individuals are also among the causes that trigger this condition. Significant negative consequences result from digital addiction, including decreased empathy skills, anxiety disorders, sleep disorders, and depression. Another common result is a decrease in academic achievement (Hamida et al., 2021; Huang, 2024; Khan et al., 2021; Vaghefi & Lapointe, 2014; Yang & Gao, 2022).

*Table 1. A Review of Literature: Analytical methods and findings*

| Authors and Year | Topic | Analytical Method | Data | Findings |
|---|---|---|---|---|
| (Dhanalakshmi et al., 2025) | The present study aims to assess the prevalence of internet and mobile addiction across all age demographics through the utilization of artificial intelligence methodologies. | Machine Learning Classification Models (Random Forest, SVM, KNN, Logistic Regression) | Internet Addiction Test (IAT) Survey (n=1763) | Artificial intelligence models can classify addiction levels (low, medium, high) from survey data with up to 71% accuracy. |
| (Parhi et al., 2025) | The utilization of digital data and soft computing techniques has emerged as a novel approach for the analysis and tracking of behavioral addiction. | Machine Learning (Logistic Regression), feature selection with Particle Swarm Optimization (PSO) | Application-Based Real-Time Usage Data (UsageStats, Activity Tracker) and Survey | Instantaneous usage data collected via applications assesses addiction more accurately than traditional surveys. A survey optimized with real-time data achieved 98.61% success in predicting nomophobia. |
| (Singh et al., 2023) | The objective of the present study is to utilize an unobtrusive method for the detection of smartphone addiction. | Rule-Based System Development, Behavioral Analysis | Passive User Data Collected via an Android Application (device unlocks, number of screen-ons, application usage time) | Addiction detection through behavioral rules derived from various methods (e.g., turning on the screen more than 110 times a day). |
| (Wu & Zhang, 2023) | A statistical model has been developed to analyze the impact of middle school students' engagement with mobile phones on their addictive tendencies. | Regression Analysis, Moderation (Interaction) Analysis | Survey Data (n=312) | Parent-child communication problems and poor peer relationships statistically strengthen this effect. |

| | | | | |
|---|---|---|---|---|
| (Yang & Gao, 2022) | This investigation utilizes longitudinal analysis to examine the correlation between smartphone addiction and basic psychological needs in a sample of middle school students. | Advanced Statistical Modeling | Survey (n=337) | The inability to meet the need for competence significantly predicts future smartphone addiction. |
| (Hamida et al., 2021) | The present study aims to explore the relationships between loneliness, smartphone addiction, and empathy among Generation Z. | Structural Equation Modeling (SEM) | Survey Data (n=253) | SEM analysis showed that smartphone addiction fully mediates the relationship between loneliness and empathy. |
| (Davazdahemami et al., 2016) | The phenomenon of device addiction is distinct from the more specific case of application addiction (referred as "app addiction"). | Structural Equation Modeling (SEM) | Survey Data (n=333) | Application addiction explains approximately 38% of the total variance in mobile device addiction. |

Table 1 presents a compendium of studies in the extant literature that employ various methodologies for the assessment of digital addiction in young individuals. A significant source of data regarding user behavior can be derived from examining smartphone usage habits. The extant literature also indicates that variables such as the time spent using applications, the total screen time, and the responses to phone notifications are significant in determining digital addiction (Dhanalakshmi et al., 2025; Parhi et al., 2025; Singh et al., 2023). In this study, the data are analyzed using machine learning methods to measure digital addiction among Generation Z. The objective of the study is to classify addiction levels, thereby identifying individuals at risk and establishing the foundation for a decision support process to develop intervention systems.

## 2. Material and Method

The study utilized a publicly available dataset, entitled the 'Teen Phone Addiction Dataset' (Yadav, 2025). The objective of the present study is to examine the effects of smartphone usage habits among students aged 12-21 across a range of dimensions and to utilize machine learning methodologies to model the correlation between digital addiction and its impact on various domains of functioning, including behavioral, psychological, and academic performance. The total sample size of the data is 3000, comprising

25 attributes. The data has been obtained through the administration of structured surveys over a three-month period in educational institutions located within urban areas. Following the removal of identifying information such as ID and Name from the dataset, the variable named 'Addiction_Level', consisting of 24 attributes, has been determined as the target variable, and all data fields are shown in Table 2.

***Table 2. Field names and types of the dataset***

| Column Name | Data Type | Column Name | Data Type |
|---|---|---|---|
| ID | int64 | Depression_Level | int64 |
| Name | object | Self_Esteem | int64 |
| Age | int64 | Parental_Control | int64 |
| Gender | object | Screen_Time_Before_Bed | float64 |
| Location | object | Phone_Checks_Per_Day | int64 |
| School_Grade | object | Apps_Used_Daily | int64 |
| Daily_Usage_Hours | float64 | Time_on_Social_Media | float64 |
| Sleep_Hours | float64 | Time_on_Gaming | float64 |
| Academic_Performance | int64 | Time_on_Education | float64 |
| Social_Interactions | int64 | Phone_Usage_Purpose | object |
| Exercise_Hours | float64 | Family_Communication | int64 |
| Anxiety_Level | int64 | Weekend_Usage_Hours | float64 |
| | | Addiction_Level | float64 |

As demonstrated in Figure 1 the median daily screen time across all age groups was found to be 4.5 hours. The distribution graph demonstrates a positive correlation between screen time and addiction. A significant correlation has been demonstrated between screen time exceeding eight hours and the development of addiction.

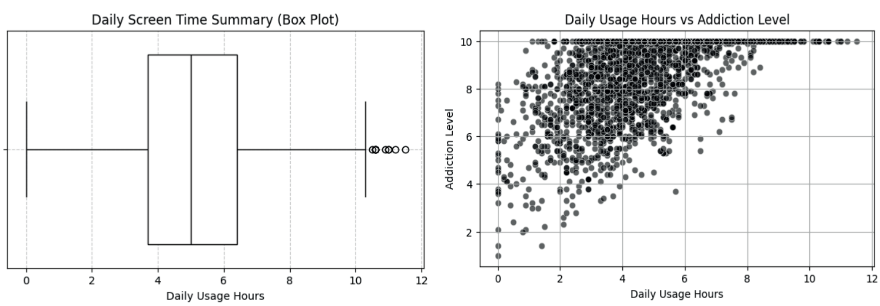


***Figure 1. A Correlation Between the Frequency of Daily Usage and the Level of Addiction***

A classification model has been developed to predict the digital addiction levels of young individuals in the dataset. The Addiction Level variable has been categorized into three distinct values: low, medium, and high. In the data preprocessing step, the categorical attributes in the data were converted to numerical values and standardized using StandardScaler. To enhance the generalizability of the data, it has been divided into training and test data at a ratio of 80% and 20%, respectively. In the field of modelling, the success of predictions has been analyzed through the utilization of various metrics, employing four distinct classification algorithms (Logistic Regression, Gradient Boosting, Neural Net (MLP), XGBoost). The outcomes of this analysis have been thoroughly evaluated.

***Table 3. Comparative metrics results for the proposed models***

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Logistic Regression | 0.99 | 0.99 | 0.99 | 0.99 |
| Gradient Boosting | 0.96 | 0.95 | 0.96 | 0.95 |
| Neural Net (MLP) | 0.96 | 0.95 | 0.96 | 0.95 |
| XGBoost | 0.94 | 0.94 | 0.94 | 0.94 |

As demonstrated in Table 3, the Logistic Regression model demonstrates superior performance in comparison to alternative models, achieving 99% accuracy and an F1-score. The investigation revealed that the models demonstrated an inability to predict the samples classified as 'Low' in the Addiction Level variable, which contained the smallest number of samples in the dataset. In this instance it has been observed that the Logistic Regression model demonstrated a superior capacity for generalization, despite the presence of an imbalanced dataset.

## 3. Conclusion

The study demonstrates that four distinct machine learning methodologies can be implemented to model behavioral phenomena in predicting the level of digital addiction among Generation Z. When the modelling prediction results are evaluated alongside similar studies in literature, it is understood that approaches such as machine learning show better prediction performance than other methods. The machine learning models presented in this study demonstrate a high level of success in classifying levels of digital addiction among Generation Z. In particular, the Logistic Regression model demonstrates a significant improvement in similar studies in literature thanks to its high classification accuracy. The findings confirm that data-driven analytical approaches are critical for developing early diagnosis and effective intervention strategies. Considering the prevalence of digital addiction among Generation Z and its associated adverse consequences, data-driven analytical methodologies have emerged as a pivotal instrument for early diagnosis and the development of effective intervention strategies. These methodologies encompass the interpretation of behavioral data and the creation of decision support systems, such as risk classification, which play a crucial role in identifying and addressing issues promptly. Subsequent studies may concentrate on the practical implementation of the model as mobile applications in real time. However, it is important to acknowledge the limitations of this study. Firstly, participant responses may have been affected by a tendency to seek social acceptance, given that data had been collected through the utilization of structured surveys. Consequently, there is a possibility that the data may not accurately reflect real-world usage habits. Research in relevant literature has shown that real-time usage data collected through smartphone applications measures addiction more accurately than alternative methods based on surveys. Furthermore, it has been observed that the imbalance in the data set has resulted in an insufficient number of sample data points from the "Low Addiction" level for the model to be correctly classified. To surpass the present limitations in future research, it is recommended to apply hybrid datasets that include real-time application data and behavioral indicators. Examples of such indicators include device unlock count and application usage duration, which are also utilized in the literature. Furthermore, rather than focusing only on behavioral metrics, the development of models integrating psychological factors including feelings of social isolation and a need for social acceptance may provide a more comprehensive framework for understanding the fundamental causes of digital addiction. This approach has the advantage of increasing the generalizability of the model, thus creating more effective decision support processes in practical environments, like mobile applications.

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# Yönetim Bilişim Sistemleri Alanında Yenilikçi Çözümler ve Güncel Yaklaşımlar – II

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