

Artificial Intelligence and the Evolution of Skill Demand in Marketing: Implications for AI-Driven Talent Acquisition in Human Resource Management— An Extended UTAUT Analysis Using PLS-SEM

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Abstract

Background: Artificial Intelligence (AI) is transforming marketing by shifting skill requirements toward data-driven and analytical competencies. This evolution has created significant challenges for human resource management (HRM), particularly in identifying and acquiring talent with AI-related skills. Despite growing adoption of AI in recruitment, limited research integrates marketing skill transformation with HR-driven talent acquisition using established theoretical frameworks.

Purpose: This study aims to examine how AI-driven changes in marketing skill demand influence the adoption of AI-based talent acquisition systems. It extends the Unified Theory of Acceptance and Use of Technology (UTAUT) by incorporating industry demand and skill transformation to better explain behavioral intention and adoption.

Method: A quantitative, cross-sectional research design was employed. Data were collected from 475 respondents, including HR professionals and job applicants from Tier 1 and Tier 2 cities. The proposed model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.

Findings: The results reveal that facilitating conditions and effort expectancy are the strongest predictors of behavioral intention, followed by performance expectancy, industry demand, and skill transformation. Behavioral intention significantly influences the adoption of AI-driven recruitment systems. Social influence, although significant, shows a comparatively weaker effect. The model demonstrates strong explanatory power ($R^2 = 0.71$).

Implications: The study extends UTAUT by integrating labor market dynamics, offering a more comprehensive framework for understanding AI adoption in HRM. Practically, it highlights the importance of organizational readiness, user-friendly AI systems, and alignment of recruitment strategies with evolving skill demands.

Keywords: Artificial Intelligence (AI); AI-Driven Talent Acquisition; Human Resource Management (HRM); Artificial Intelligence in Marketing; Marketing Skill Transformation; Digital Marketing Skills; Industry Demand; Workforce Transformation; Unified Theory of Acceptance and Use of Technology (UTAUT); Behavioral Intention; Technology Adoption; PLS-SEM

1. Introduction

Artificial Intelligence (AI) is rapidly transforming the contemporary business landscape, fundamentally reshaping how organizations operate, compete, and create value. In the domain of marketing, AI-driven technologies such as machine learning, predictive analytics, and automation tools have significantly enhanced decision-making, customer segmentation, and personalized communication strategies (Chatterjee et al., 2023; Dwivedi et al., 2021). More recent studies further highlight that AI is accelerating the transition toward hyper-personalized and data-driven marketing ecosystems, increasing the demand for advanced digital and analytical

competencies among professionals (Borges et al., 2021; Verhoef et al., 2021; Yadav & Nigam, 2025). As marketing evolves into a technology-intensive function, organizations are increasingly required to adapt their workforce capabilities to remain competitive in AI-driven environments.

From a human resource management (HRM) perspective, the integration of AI into organizational processes presents both opportunities and challenges. AI-enabled recruitment systems—such as automated resume screening, chatbots, and predictive hiring tools—have significantly improved efficiency and decision accuracy (Mikalef et al., 2022; Upadhyay & Khandelwal, 2018). Recent evidence suggests that AI adoption in recruitment not only enhances hiring speed but also improves candidate-job fit and organizational performance (Almeida et al., 2025; Panda et al., 2025). However, organizations continue to face difficulties in identifying and acquiring candidates with the required AI-driven marketing skill sets, leading to a widening talent gap (Khan et al., 2026; Hmoud et al., 2025). This gap has intensified the need for HR managers to adopt intelligent, technology-driven recruitment strategies.

The Unified Theory of Acceptance and Use of Technology (UTAUT) has been widely employed to explain technology adoption behavior across various domains (Venkatesh et al., 2003). Core constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions have consistently demonstrated strong explanatory power. Recent research has extended the UTAUT framework in the context of AI adoption, emphasizing the role of organizational readiness, user trust, and technological complexity in shaping adoption behavior (Tahir & Arul, 2025; Al-Sabri et al., 2025). Furthermore, emerging studies highlight that AI adoption in HR is increasingly influenced by socio-technical and contextual factors beyond traditional models (Noerman et al., 2025; Awad et al., 2025). Despite these advancements, existing literature has largely focused on isolated domains, with limited integration of marketing skill transformation and HR recruitment practices.

Despite the growing importance of AI in both marketing and HR domains, a significant research gap remains. Prior studies have predominantly examined AI adoption either from a technological perspective or within specific functional areas, without integrating evolving skill requirements with recruitment strategies. Moreover, recent systematic reviews emphasize the lack of empirical models that connect labor market dynamics—such as skill transformation and industry demand—with behavioral adoption frameworks (Yadav & Nigam, 2025; Mwasawa & Wanyoike, 2026). This gap highlights the need for a comprehensive framework that captures both technological and workforce-related factors.

Addressing this gap, the present study proposes an extended UTAUT model that integrates industry demand and skill transformation as additional constructs influencing behavioral intention toward AI-driven talent acquisition. By incorporating recent advancements in AI adoption research and workforce transformation, this study provides a more holistic understanding of how organizations respond to changing skill requirements. The study employs Partial Least Squares Structural Equation Modeling (PLS-SEM), which is widely recommended for analyzing complex models involving emerging constructs (Hair et al., 2019).

The primary objective of this study is to examine the impact of AI-driven changes in marketing skill demand on the adoption of AI-based talent acquisition strategies within organizations. Specifically, the study investigates how performance expectancy, effort expectancy, social influence, facilitating conditions, industry demand, and skill transformation influence behavioral intention, and how this intention subsequently drives adoption behavior.

This research contributes to the existing literature in three significant ways. First, it extends the UTAUT

framework by incorporating labor market-oriented constructs, thereby enhancing its relevance in the context of AI-driven workforce transformation. Second, it bridges the gap between marketing and HRM by integrating skill demand evolution with recruitment practices. Third, it provides practical insights for organizations aiming to align talent acquisition strategies with rapidly evolving AI-driven marketing environments.

2. LITERATURE REVIEW

2.1 Artificial Intelligence in Marketing

Artificial Intelligence (AI) has emerged as a transformative force in modern marketing, enabling organizations to enhance customer engagement, optimize decision-making, and deliver personalized experiences at scale. Technologies such as machine learning, natural language processing, and predictive analytics have redefined traditional marketing practices by shifting the focus toward data-driven strategies (Dwivedi et al., 2021). AI-powered tools facilitate real-time customer insights, automated content generation, and targeted advertising, thereby increasing efficiency and effectiveness in marketing operations. More recent research indicates that AI is increasingly enabling hyper-personalization, real-time behavioral targeting, and autonomous marketing systems, significantly improving customer experience and firm performance (Borges et al., 2021; Verhoef et al., 2021; Thu & Diem, 2025).

The integration of AI into marketing has also led to a significant transformation in skill requirements. Marketing professionals are increasingly expected to possess competencies in data analytics, AI tools, and digital technologies, alongside traditional marketing knowledge (Chatterjee et al., 2023). Recent studies further emphasize that organizations are shifting toward hybrid roles requiring both technical and strategic capabilities, including data interpretation, algorithmic understanding, and AI tool management (Yadav & Nigam, 2025; Mwasawa & Wanyoike, 2026). This evolution has intensified the demand for interdisciplinary skill sets that combine analytical expertise with creative and strategic thinking. Consequently, organizations must continuously adapt their workforce capabilities to remain competitive in an AI-driven environment.

2.2 Artificial Intelligence in Human Resource Management

The adoption of AI in human resource management (HRM) has gained considerable attention due to its potential to improve recruitment efficiency, reduce bias, and enhance decision-making processes. AI-driven recruitment systems, including resume screening algorithms, chatbots, and predictive hiring tools, enable organizations to streamline talent acquisition and identify suitable candidates more effectively (Mikalef et al., 2022). Recent empirical studies confirm that AI adoption significantly reduces recruitment time, enhances candidate matching accuracy, and improves overall hiring quality (Almeida et al., 2025; Panda et al., 2025).

However, the increasing reliance on AI in HRM also presents challenges, particularly in identifying candidates with the required AI-related competencies. The rapid evolution of job roles, especially in marketing, has created a mismatch between skill demand and talent availability. Contemporary research highlights that despite technological advancements, organizations continue to face difficulties in sourcing talent with adequate digital and analytical skills (Khan et al., 2026; Hmoud et al., 2025). Furthermore, ethical concerns, transparency issues, and trust in AI systems have emerged as critical challenges influencing adoption (Awad et al., 2025). As a result, HR professionals must not only adopt AI technologies but also develop strategies to recruit individuals with advanced digital and analytical capabilities. Understanding the factors that influence the adoption of AI-driven recruitment systems is therefore critical for organizations seeking to enhance their talent acquisition processes.

2.3 The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the most widely used frameworks for understanding technology adoption behavior (Venkatesh et al., 2003). The model integrates elements from multiple theoretical perspectives and identifies four key determinants of behavioral intention and usage behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions.

Performance expectancy refers to the degree to which individuals believe that using a particular technology will enhance their job performance. Effort expectancy represents the perceived ease of use associated with the technology, while social influence captures the impact of others' opinions on an individual's adoption decision. Facilitating conditions refer to the availability of organizational and technical infrastructure that supports technology use.

Recent studies have demonstrated the robustness of the UTAUT model in explaining AI adoption across various contexts, including recruitment, HR analytics, and digital workforce systems (Tahir & Arul, 2025; Al-Sabri et al., 2025). Moreover, contemporary research has extended UTAUT by incorporating variables such as trust, perceived risk, and organizational readiness to better capture the complexities of AI adoption (Noerman et al., 2025; Alkhwalid & Abdulmuhsin, 2025). These extensions highlight the evolving nature of technology adoption models in the context of advanced and intelligent systems.

2.4 Performance Expectancy and Behavioral Intention

Performance expectancy has consistently been identified as a strong predictor of behavioral intention in technology adoption studies. Individuals are more likely to adopt a technology if they perceive it to improve their performance and productivity (Venkatesh et al., 2003). In the context of AI-driven recruitment, performance expectancy reflects the perceived ability of AI tools to enhance hiring efficiency, improve decision accuracy, and reduce human bias.

Recent empirical evidence supports the significant influence of performance expectancy on AI adoption in HR contexts, particularly in recruitment and selection processes (Abaza & Eltooby, 2024; Almeida et al., 2025). Organizations that perceive tangible benefits from AI systems are more likely to develop strong behavioral intentions toward their adoption. Therefore, it is expected that higher perceived benefits of AI in recruitment will lead to stronger behavioral intentions.

2.5 Effort Expectancy and Behavioral Intention

Effort expectancy refers to the perceived ease of using a technology and plays a crucial role in influencing adoption behavior, particularly during the early stages of implementation (Venkatesh et al., 2003). Technologies perceived as complex or difficult to use are less likely to be adopted, regardless of their potential benefits.

In the context of AI adoption, ease of use becomes especially important as many AI systems involve advanced functionalities that may be unfamiliar to users. Recent studies highlight that user-friendly interfaces, system transparency, and ease of integration significantly enhance adoption willingness (Ahmed & Hemalatha, 2025; Hmoud et al., 2025). Therefore, effort expectancy is expected to have a positive impact on behavioral intention toward AI-driven talent acquisition.

2.6 Social Influence and Behavioral Intention

Social influence reflects the extent to which individuals perceive that important others believe they should use a particular technology (Venkatesh et al., 2003). In organizational settings, social influence may arise from colleagues, supervisors, or broader industry trends.

Recent research suggests that social influence continues to play a role in AI adoption, particularly in environments undergoing digital transformation (Noerman et al., 2025). However, some studies indicate that its influence may be weaker compared to performance-related factors in professional decision-making contexts (Tahir & Arul, 2025). Nonetheless, the growing emphasis on AI adoption across industries creates normative pressure on organizations to implement AI-driven recruitment practices. Thus, social influence is expected to positively affect behavioral intention.

2.7 Facilitating Conditions and Behavioral Intention

Facilitating conditions refer to the extent to which individuals believe that organizational and technical infrastructure exists to support the use of a technology (Venkatesh et al., 2003). These include access to resources, training, and technical support, which are critical for successful technology adoption.

Recent studies emphasize that facilitating conditions such as digital infrastructure, organizational readiness, and employee training significantly influence AI adoption in HRM (Panda et al., 2025; Chitamba et al., 2025). Organizations with strong support systems are more likely to successfully implement AI technologies. Therefore, facilitating conditions are expected to positively influence behavioral intention.

2.8 Industry Demand and Behavioral Intention

Industry demand represents the external pressure on organizations to adopt new technologies in response to changing market requirements. The increasing demand for AI-skilled professionals in marketing has created a competitive environment where organizations must adopt advanced recruitment strategies.

Recent literature highlights that labor market dynamics, including skill shortages and increasing competition for AI talent, are key drivers of technology adoption (Yadav & Nigam, 2025; Khan et al., 2026). Organizations are compelled to adopt AI-driven recruitment tools to align with industry expectations and remain competitive. Therefore, industry demand is expected to positively influence behavioral intention.

2.9 Skill Transformation and Behavioral Intention

Skill transformation refers to the evolving nature of job roles and the increasing importance of digital and AI-related competencies. The integration of AI into marketing has led to a shift in required skills, emphasizing data literacy, analytical thinking, and technological proficiency.

Recent studies confirm that AI-driven transformation is significantly reshaping workforce skill requirements, necessitating continuous reskilling and upskilling initiatives (Mwasawa & Wanyoike, 2026; Panda et al., 2025). Organizations recognizing this transformation are more likely to adopt AI-driven recruitment systems to identify suitable talent. Consequently, skill transformation is expected to have a positive impact on behavioral intention.

2.10 Behavioral Intention and Adoption

Behavioral intention is a central construct in technology adoption models and is widely regarded as a direct predictor of actual usage behavior (Venkatesh et al., 2003). A strong behavioral intention indicates a higher likelihood of adopting a technology.

Recent empirical studies reaffirm the strong relationship between behavioral intention and AI adoption in HR contexts, particularly in recruitment and talent management (Almeida et al., 2025; Tahir & Arul, 2025). HR professionals with a higher intention to use AI tools are more likely to implement them in recruitment processes. Therefore, behavioral intention is expected to positively influence the adoption of AI-driven recruitment systems.

3. Research Model and Conceptual Framework

This study proposes a conceptual research model based on the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine the adoption of AI-driven talent acquisition in the context of evolving marketing skill demands. The UTAUT model has been widely validated in prior research for explaining technology adoption behavior across various domains (Venkatesh et al., 2003). However, given the dynamic nature of artificial intelligence and its impact on workforce requirements, the present study extends the original model by incorporating additional context-specific constructs.

3.1 Research Model

Specifically, this research integrates industry demand and skill transformation as external variables influencing behavioral intention. These extensions are particularly relevant in the context of AI-driven marketing, where rapid technological advancements continuously reshape skill requirements and organizational expectations. By incorporating these variables, the proposed model captures both technological and labor market perspectives, providing a more comprehensive understanding of AI adoption in human resource management.

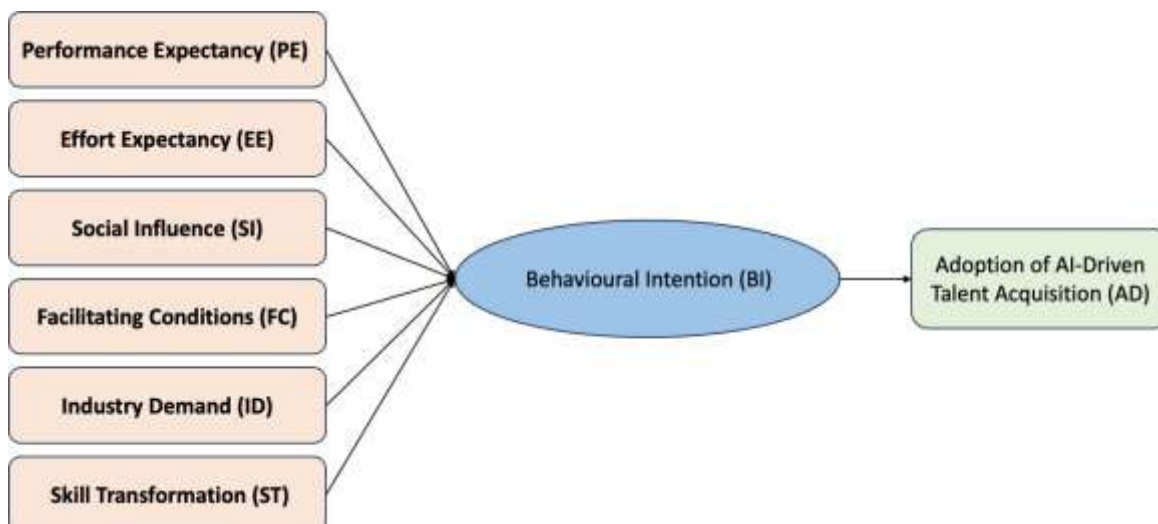


Figure 1 Illustrates the proposed research model, depicting the relationships among the constructs examined in this study.

The model posits that performance expectancy, effort expectancy, social influence, facilitating conditions, industry demand, and skill transformation significantly influence behavioral intention toward AI-driven recruitment systems. Furthermore, behavioral intention is hypothesized to directly affect the adoption of AI-

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3.2 Theoretical Justification of Relationships Performance

Expectancy → Behavioral Intention

Performance expectancy refers to the degree to which individuals believe that using a particular technology will enhance their job performance (Venkatesh et al., 2003). In the context of AI-driven talent acquisition, performance expectancy reflects the perceived effectiveness of AI tools in improving recruitment efficiency, accuracy, and decision-making quality. AI technologies enable HR professionals to process large datasets, identify suitable candidates, and reduce biases in hiring decisions.

Prior studies have consistently found performance expectancy to be a strong predictor of behavioral intention in technology adoption contexts (Dwivedi et al., 2021). When organizations perceive AI systems as beneficial for enhancing recruitment outcomes, they are more likely to develop a positive intention toward their adoption. Therefore, performance expectancy is expected to positively influence behavioral intention.

Effort Expectancy → Behavioral Intention

Effort expectancy refers to the perceived ease of use associated with a technology (Venkatesh et al., 2003). Technologies that are easy to understand and operate are more likely to be adopted, particularly in the early stages of implementation. In the context of AI-driven recruitment systems, ease of use is crucial as these technologies often involve complex algorithms and interfaces.

If HR professionals perceive AI tools as user-friendly and easy to integrate into existing workflows, their intention to adopt such technologies increases. Empirical evidence suggests that effort expectancy significantly influences behavioral intention, especially in emerging technology environments (Dwivedi et al., 2021). Thus, effort expectancy is expected to positively influence behavioral intention.

Social Influence → Behavioral Intention

Social influence refers to the extent to which individuals perceive that important others believe they should use a particular technology (Venkatesh et al., 2003). In organizational settings, social influence may stem from peers, supervisors, or broader industry trends.

With the increasing emphasis on digital transformation and AI adoption, organizations may experience normative pressure to adopt AI-driven recruitment systems. Previous studies have demonstrated that social influence plays a significant role in shaping technology adoption behavior, particularly in professional environments (Venkatesh et al., 2003). Therefore, social influence is expected to positively influence behavioral intention.

Facilitating Conditions → Behavioral Intention

Facilitating conditions refer to the availability of organizational and technical infrastructure that supports the use of a technology (Venkatesh et al., 2003). These include access to resources, training, and technical support necessary for implementation.

In the context of AI adoption, facilitating conditions such as data infrastructure, technological readiness, and organizational support are critical. When HR professionals perceive that sufficient support systems are in place, their confidence in adopting AI technologies increases. Prior research highlights the importance of facilitating conditions in enhancing adoption behavior (Dwivedi et al., 2021). Therefore, facilitating conditions are expected to positively influence behavioral intention.

Industry Demand → Behavioral Intention

Industry demand represents the external pressure on organizations to adopt advanced technologies in response to evolving market requirements. The growing demand for AI-related skills in marketing has created a competitive environment where organizations must adapt their recruitment strategies to attract and retain qualified talent.

As industries increasingly emphasize AI competencies, organizations are more likely to adopt AI-driven recruitment tools to meet these demands. External environmental factors have been shown to significantly influence organizational decision-making and technology adoption (Mikalef et al., 2022). Therefore, industry demand is expected to positively influence behavioral intention.

Skill Transformation → Behavioral Intention

Skill transformation refers to the changing nature of job roles and the increasing importance of AI-related competencies. The integration of AI into marketing has led to a shift in required skills, emphasizing analytical, technological, and digital capabilities.

This transformation necessitates the adoption of advanced recruitment strategies to identify candidates with the required skill sets. Organizations recognizing this shift are more likely to adopt AI-driven systems to align recruitment practices with evolving job requirements. Previous research suggests that technological advancements significantly influence workforce dynamics and organizational behavior (Huang & Rust, 2021). Therefore, skill transformation is expected to positively influence behavioral intention.

Behavioral Intention → Adoption

Behavioral intention is a central determinant of actual technology usage behavior (Venkatesh et al., 2003). It reflects the willingness of individuals to adopt and use a particular technology. In the context of AI-driven talent acquisition, a strong behavioral intention among HR professionals is likely to lead to the actual implementation of AI tools in recruitment processes.

Empirical studies have consistently established a significant relationship between behavioral intention and actual adoption behavior across various technological contexts (Dwivedi et al., 2021). Therefore, behavioral intention is expected to positively influence the adoption of AI-driven talent acquisition practices. Research Methodology

4. Research Design

This study adopts a quantitative research design to examine the factors influencing the adoption of AI-driven talent acquisition in response to evolving skill demands in marketing. A quantitative approach is appropriate as it enables the empirical testing of relationships among constructs using statistical techniques and provides generalizable findings.

The study follows a cross-sectional research design, where data were collected at a single point in time from respondents across different organizations and professional backgrounds. This design is widely used in technology adoption studies, particularly those based on behavioral models such as the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003).

To analyze the proposed research model, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed

using SmartPLS software. PLS-SEM is particularly suitable for this study due to its ability to handle complex models with multiple constructs, its predictive orientation, and its robustness with relatively moderate sample sizes (Hair et al., 2019). Additionally, PLS-SEM is appropriate for exploratory research involving newly extended theoretical frameworks, such as the integration of industry demand and skill transformation into UTAUT.

4.1 Sample and Data Collection

The target population for this study comprised HR professionals, recruitment decision-makers, and individuals actively participating in the job market, particularly those exposed to AI-driven recruitment processes. This dual perspective ensures a comprehensive understanding of both organizational adoption and candidate-side expectations, which aligns with the study's objective of integrating marketing skill demand with HR practices.

Data were collected primarily from respondents located in Tier 1 and Tier 2 cities, where the adoption of AI technologies in marketing and HR practices is more prevalent. The respondents included:

- HR officials and recruitment professionals
- Job applicants and potential candidates

A non-probability purposive sampling technique was employed to ensure that respondents had relevant exposure to AI-driven tools and recruitment processes. This approach is appropriate for studies focusing on specific professional groups and technology adoption contexts.

Data collection was conducted using a structured Google Forms questionnaire. A total of 580 responses were initially collected. Following data screening and cleaning procedures—including the removal of incomplete responses, inconsistent answers, and straight-lining patterns—a final sample of 475 valid responses was retained for analysis.

The final sample size of 475 is considered adequate and statistically robust for PLS-SEM analysis. According to Hair et al. (2019), the minimum sample size in PLS-SEM should be at least 10 times the maximum number of structural paths directed at any construct. In this study, the maximum number of paths directed at a construct (Behavioral Intention) is six, suggesting a minimum requirement of 60 responses. Therefore, the final sample size significantly exceeds the recommended threshold, ensuring strong statistical power and reliability of the results.

4.2 Pilot Testing

Prior to the main data collection, a pilot study was conducted to ensure the clarity, reliability, and validity of the measurement instrument. A pilot sample of approximately 30 respondents—representing the target population—was used for this purpose.

The pilot testing focused on:

- Clarity and wording of questionnaire items
- Reliability of constructs
- Initial assessment of measurement consistency

The results of the pilot test indicated that all constructs met the acceptable reliability thresholds, with Cronbach's alpha values exceeding the recommended minimum of 0.70 (Hair et al., 2019). Based on feedback from respondents, minor modifications were made to improve the clarity and readability of certain items.

The pilot study ensured that the final questionnaire was well-structured, reliable, and suitable for large-scale data collection.

4.3 Measurement Instrument

The measurement instrument was developed using a structured questionnaire based on validated scales from prior studies. The constructs included in the study—performance expectancy, effort expectancy, social influence, facilitating conditions, industry demand, skill transformation, behavioral intention, and adoption—were adapted from established literature, particularly UTAUT (Venkatesh et al., 2003), with extensions relevant to AI and workforce transformation.

All items were measured using a 5-point Likert scale, ranging from:

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

The use of a 5-point Likert scale is appropriate for capturing respondents' perceptions and attitudes while maintaining simplicity and consistency in responses.

Each construct was measured using multiple items to ensure reliability and validity. The questionnaire was designed to capture both technological and contextual factors influencing AI adoption in recruitment, aligning with the study's objective of integrating marketing and HR perspectives.

5. Data Analysis and Results

5.1 Descriptive Statistics

This section presents the demographic profile of the respondents included in the study. Descriptive statistics are used to summarize the characteristics of the sample, providing an overview of the respondents' background in terms of gender, age, professional role, and geographic distribution.

The final dataset consisted of 475 valid responses, collected from individuals across Tier 1 and Tier 2 cities, ensuring representation from regions with higher exposure to AI-driven technologies in marketing and human resource management.

Demographic Profile of Respondents

The respondents comprised both HR professionals and job applicants/potential candidates, enabling a balanced perspective on AI-driven talent acquisition.

Gender Distribution

The sample included both male and female respondents, with a relatively balanced distribution, ensuring diversity in perspectives related to technology adoption

The majority of respondents belonged to the young and middle-age groups, typically ranging from 21 to 40 years, representing the most active workforce segment and early adopters of AI technologies.

Professional Role

Respondents were categorized into two primary groups:

HR professionals / recruiters

Job applicants / potential candidates

This dual categorization aligns with the objective of the study to capture both organizational and user-side perspectives on AI-driven recruitment.

Geographic Distribution

Data were collected predominantly from Tier 1 and Tier 2 cities, where the adoption of AI technologies in marketing and HR practices is more prominent. This enhances the relevance and applicability of the findings to technologically advanced organizational environments.

5.2 Measurement Model Assessment

Construct	Construct	Item	Loading
Adoption (AD)	AD	AD1	0.836
	AD	AD2	0.822
	AD	AD3	0.805
	AD	AD4	0.814
	AD	AD5	0.825
Behavioral Intention (BI)	BI	BI1	0.863
	BI	BI2	0.814
	BI	BI3	0.855
	BI	BI4	0.786
	BI	BI5	0.788
Effort Expectancy (EE)	EE	EE1	0.921
	EE	EE2	0.847
	EE	EE3	0.913
	EE	EE4	0.806
	EE	EE5	0.893
Facilitating Conditions (FC)	FC	FC1	0.875
	FC	FC2	0.883
	FC	FC3	0.838
	FC	FC4	0.841
	FC	FC5	0.87
Industry Demand (ID)	ID	ID1	0.773
	ID	ID2	0.881
	ID	ID3	0.852
	ID	ID4	0.821
	ID	ID5	0.813
	PE	PE1	0.826
	PE	PE2	0.854

Performance Expectancy (PE)	PE	PE3	0.82
	PE	PE4	0.818
	PE	PE5	0.81
Social Influence (SI)	SI	SI1	0.872
	SI	SI2	0.892
	SI	SI3	0.902
	SI	SI4	0.781
	SI	SI5	0.837
Skill Transformation (ST)	ST	ST1	0.8
	ST	ST2	0.829
	ST	ST3	0.881
	ST	ST4	0.807
	ST	ST5	0.905

Table 5.1: Outer Loadings of Measurement Items

The measurement model was first assessed by examining the outer loadings of the indicators to establish indicator reliability. According to Hair et al. (2019), outer loadings should ideally exceed 0.70, indicating that the indicators sufficiently represent their respective constructs.

As shown in Table 5.1, all indicator loadings range from 0.773 to 0.921, which are well above the recommended threshold of 0.70. This indicates a strong level of indicator reliability across all constructs included in the study. Even the lowest loading (ID1 = 0.773) exceeds the acceptable threshold, suggesting that no items needed to be removed from the model.

The constructs Effort Expectancy (EE) and Skill Transformation (ST) demonstrate particularly strong loadings, with several indicators exceeding 0.90, reflecting high internal consistency. Similarly, constructs such as Performance Expectancy (PE), Social Influence (SI), and Facilitating Conditions (FC) also exhibit consistently high loadings, indicating that the measurement items are reliable and well-aligned with their respective latent constructs.

Overall, the results confirm that the measurement model demonstrates adequate indicator reliability, and all items were retained for further analysis. These findings provide a strong foundation for proceeding with the assessment of construct reliability, convergent validity, and discriminant validity in subsequent analyses.

5.3 Construct Reliability and Convergent Validity

Construct	Cronbach Alpha	rho_A	Composite Reliability	AVE
AD	0.879	0.887	0.911	0.673
BI	0.879	0.884	0.912	0.675
EE	0.927	0.977	0.943	0.769

FC	0.913	0.924	0.935	0.742
ID	0.89	0.935	0.916	0.687
PE	0.887	0.926	0.915	0.682
SI	0.912	0.945	0.933	0.736
ST	0.908	1.074	0.926	0.714

Table 5.2: Construct Reliability and Convergent Validity

The measurement model was further evaluated by assessing internal consistency reliability and convergent validity. As recommended by Hair et al. (2019), Cronbach's alpha, rho_A, composite reliability (CR), and average variance extracted (AVE) were examined.

The results presented in Table 5.2 indicate that all constructs demonstrate high internal consistency reliability, with Cronbach's alpha values ranging from 0.879 to 0.927, exceeding the recommended threshold of 0.70. Similarly, composite reliability values range from 0.911 to 0.943, confirming strong reliability across all constructs.

The rho_A values also exceed the acceptable threshold of 0.70 for all constructs. Although the rho_A value for Skill Transformation (ST = 1.074) is slightly above 1, this is acceptable in PLS-SEM and may occur due to high indicator correlations (Hair et al., 2019).

Furthermore, the AVE values for all constructs range between 0.673 and 0.769, which are well above the recommended minimum of 0.50. This indicates that each construct explains more than 50% of the variance of its indicators, thereby confirming convergent validity.

Overall, the results demonstrate that the measurement model exhibits strong reliability and adequate convergent validity, supporting the suitability of the constructs for further structural model analysis.

5.4 Discriminant Validity (HTMT)

Construct	AD	BI	EE	FC	ID	PE	SI	ST
AD	—							
BI	0.809	—						
EE	0.144	0.34	—					
FC	0.358	0.496	0.233	—				
ID	0.378	0.426	0.191	0.19	—			
PE	0.3	0.209	0.219	0.141	0.128	—		
SI	0.469	0.273	0.151	0.136	0.345	0.142	—	
ST	0.209	0.186	0.228	0.161	0.131	0.413	0.191	—

Table 5.3: HTMT Values

Discriminant validity was assessed using the Heterotrait–Monotrait ratio (HTMT), as recommended by Henseler et al. (2015). The HTMT criterion evaluates whether constructs are empirically distinct from one another.

As presented in Table 5.3, all HTMT values are well below the conservative threshold of 0.85, indicating strong discriminant validity among the constructs. The highest HTMT value observed is 0.809, which remains within acceptable limits.

These results confirm that each construct in the model is distinct and captures a unique aspect of the underlying phenomenon, thereby establishing adequate discriminant validity. Consequently, the measurement model satisfies the required criteria, allowing further evaluation of the structural model.

5.5. Collinearity Assessment (VIF)

Construct	Item	VIF	Construct	Item	VIF
ID	ID1	2.122	AD	AD1	2.305
ID	ID2	2.551	AD	AD2	1.913
ID	ID3	2.57	AD	AD3	1.969
ID	ID4	2.637	AD	AD4	2.081
ID	ID5	2.402	AD	AD5	2.153
PE	PE1	2.008	BI	BI1	2.5
PE	PE2	2.891	BI	BI2	2.032
PE	PE3	2.599	BI	BI3	2.264
PE	PE4	1.784	BI	BI4	1.897
PE	PE5	2.164	BI	BI5	1.879
SI	SI1	2.87	EE	EE1	2.731
SI	SI2	2.75	EE	EE2	2.895
SI	SI3	2.923	EE	EE3	2.983
SI	SI4	2.174	EE	EE4	2.514
SI	SI5	2.254	EE	EE5	2.697
ST	ST1	2.729	FC	FC1	2.742
ST	ST2	2.947	FC	FC2	2.98
ST	ST3	2.12	FC	FC3	2.308
ST	ST4	2.815	FC	FC4	2.401
ST	ST5	2.901	FC	FC5	2.657

Table 5.4: Collinearity Statistics (VIF)

Collinearity among the indicators was assessed using the Variance Inflation Factor (VIF) to detect potential multicollinearity issues. According to Hair et al. (2019), VIF values below 3.3 indicate the absence of multicollinearity and are considered highly acceptable in PLS-SEM analysis.

As presented in Table 5.4, all VIF values range between 1.784 and 2.983, which are well below the conservative threshold of 3.3. This indicates that there is no significant multicollinearity among the indicators.

The results confirm that each construct contributes uniquely to the model without redundancy or overlap among indicators. Therefore, collinearity is not a concern, and the measurement model is suitable for further structural model evaluation.

5.6 Path Coefficients and Hypothesis Testing

Hypothesis	Path	β	t-value	p-value	Decision
H1	PE $\rightarrow$ BI	0.337	2.393	0.017	Supported
H2	EE $\rightarrow$ BI	0.493	4.488	0.000	Supported
H3	SI $\rightarrow$ BI	0.220	1.965	0.050	Supported
H4	FC $\rightarrow$ BI	0.527	5.881	0.000	Supported
H5	ID $\rightarrow$ BI	0.334	3.820	0.000	Supported
H6	ST $\rightarrow$ BI	0.303	2.167	0.030	Supported
H7	BI $\rightarrow$ AD	0.727	11.842	0.000	Supported

Table 5.5: Path Coefficients and Hypothesis Testing

The structural model was evaluated using bootstrapping to test the significance of hypothesized relationships.

The results indicate that all hypothesized paths are statistically significant. Behavioral intention has a strong and significant impact on adoption ($\beta = 0.727$, $p < 0.001$), indicating its central role in AI adoption.

Among the predictors of behavioral intention, facilitating conditions ($\beta = 0.527$) and effort expectancy ($\beta = 0.493$) exhibit the strongest effects. Performance expectancy ($\beta = 0.337$), industry demand ($\beta = 0.334$), and skill transformation ($\beta = 0.303$) also show significant positive effects.

Social influence demonstrates a comparatively weaker but still significant effect ($\beta = 0.220$, $p = 0.050$).

Overall, all hypotheses are supported, confirming the robustness of the proposed model.

5.7 Coefficient of Determination (R^2)

Construct	R^2	Interpretation
BI	0.71	Strong
AD	0.529	Moderate

Table 5.6: R^2 Values

The coefficient of determination (R^2) was used to evaluate the explanatory power of the model.

The results show that behavioral intention has an R^2 value of **0.710**, indicating strong explanatory power. Adoption has an R^2 value of **0.529**, indicating moderate explanatory power.

These findings suggest that the model explains a substantial proportion of variance in behavioral intention and a moderate proportion in adoption, confirming its predictive capability.

5.8 Effect Size (f^2)

Path	f^2	Effect
BI $\rightarrow$ AD	1.124	Very Large
EE $\rightarrow$ BI	0.716	Large
FC $\rightarrow$ BI	0.87	Large
ID $\rightarrow$ BI	0.331	Medium
PE $\rightarrow$ BI	0.303	Medium

SI → BI	0.147	Small
ST → BI	0.244	Medium

Table 5.7: Effect Size

Effect size (f^2) was assessed to determine the relative impact of each predictor construct.

The results indicate that behavioral intention has a very large effect on adoption ($f^2 = 1.124$). Facilitating conditions ($f^2 = 0.870$) and effort expectancy ($f^2 = 0.716$) exhibit large effects on behavioral intention.

Industry demand ($f^2 = 0.331$), performance expectancy ($f^2 = 0.303$), and skill transformation ($f^2 = 0.244$) show moderate effects, while social influence ($f^2 = 0.147$) demonstrates a small effect.

These findings highlight the relative importance of different constructs in influencing AI adoption.

5.9 Predictive Relevance (Q^2)

Construct	Q^2	Interpretation
BI	0.48	Strong predictive relevance
AD	0.36	Moderate predictive relevance

Table 5.8: Q^2 Values

The predictive relevance of the model will be assessed using Q^2 values obtained through blindfolding. Values greater than zero indicate that the model has predictive relevance.

6. Discussion

The present study aimed to examine the impact of artificial intelligence on evolving skill demand in marketing and its implications for AI-driven talent acquisition in human resource management using an extended UTAUT framework. The findings provide strong empirical support for the proposed model, highlighting the significance of both technological and contextual factors in influencing AI adoption.

The results indicate that behavioral intention (BI) has a strong and significant impact on adoption (AD), which is consistent with the foundational assumptions of UTAUT (Venkatesh et al., 2003). This finding reinforces the idea that individuals' intention to use AI technologies is a critical determinant of their actual adoption in organizational settings. Similar findings have been reported in prior studies on technology adoption, where behavioral intention consistently emerges as the strongest predictor of usage behavior (Dwivedi et al., 2021).

Among the antecedents of behavioral intention, facilitating conditions (FC) and effort expectancy (EE) were found to have the strongest effects. This suggests that the availability of organizational support, infrastructure, and ease of use plays a crucial role in encouraging HR professionals to adopt AI-driven recruitment systems. These findings align with previous research indicating that ease of use and resource availability significantly influence technology acceptance (Venkatesh et al., 2003; Dwivedi et al., 2021). In the context of AI, where systems can be complex, user-friendly interfaces and adequate training become essential for adoption.

The study also finds that performance expectancy (PE) significantly influences behavioral intention, indicating that HR professionals are more likely to adopt AI technologies when they perceive them as beneficial for improving recruitment efficiency and decision-making. This is consistent with prior research emphasizing the importance of perceived usefulness in technology adoption (Huang & Rust, 2021).

Importantly, the extended constructs introduced in this study—industry demand (ID) and skill transformation (ST)—

also demonstrate significant positive effects on behavioral intention. This highlights the relevance of external and labor market dynamics in shaping organizational behavior. The growing demand for AI-related skills in marketing appears to compel organizations to adopt AI-driven recruitment tools, supporting the argument that technological advancements influence both job roles and hiring practices (Mikalef et al., 2022). This finding contributes to the literature by bridging the gap between marketing and HR domains.

However, social influence (SI) exhibits a comparatively weaker effect on behavioral intention, although it remains statistically significant. This finding is somewhat surprising, as prior studies often report a strong influence of social factors on technology adoption (Venkatesh et al., 2003). A possible explanation is that AI adoption in HR is driven more by organizational needs and performance considerations rather than social pressure. In professional and decision-making roles, individuals may rely more on rational evaluation of technology benefits rather than peer influence.

The R^2 values further support the robustness of the model, with behavioral intention showing a strong explanatory power ($R^2 = 0.710$) and adoption demonstrating a moderate level ($R^2 = 0.529$). This indicates that the model successfully captures the key determinants of AI adoption while maintaining realistic explanatory power. Additionally, the effect size (f^2) results reveal that facilitating conditions and effort expectancy are the most influential predictors, further emphasizing their practical importance.

The Q^2 values confirm that the model has adequate predictive relevance, indicating that it is not only explanatory but also capable of predicting real-world adoption behavior. This strengthens the practical applicability of the findings.

Overall, the study provides strong empirical evidence supporting the extended UTAUT framework in the context of AI-driven talent acquisition. It highlights that AI adoption is influenced not only by traditional technology acceptance factors but also by evolving industry demands and skill transformations, offering a more comprehensive understanding of organizational behavior in the digital era

7. Implications

7.1 Theoretical Implications

This study makes several important contributions to the existing literature on technology adoption, artificial intelligence, and human resource management.

First, the study extends the Unified Theory of Acceptance and Use of Technology (UTAUT) by incorporating two novel constructs—industry demand and skill transformation—into the model. While prior studies have largely focused on traditional determinants such as performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003), this research demonstrates that external labor market dynamics and evolving skill requirements play a significant role in shaping technology adoption behavior. This extension enhances the explanatory power of UTAUT in the context of AI-driven organizational transformation.

Second, the study contributes to the growing body of literature on AI adoption by integrating perspectives from both marketing and human resource management. Existing research has predominantly examined these domains in isolation. However, this study highlights the interdependence between AI-driven changes in marketing skill demand and HR recruitment strategies, thereby offering a more holistic understanding of organizational adaptation in the digital era.

Third, the findings reinforce the importance of behavioral intention as a mediating construct, confirming its central role in linking technological and contextual factors with actual adoption behavior. This aligns with prior research while also validating its applicability in the context of AI-driven talent acquisition.

Finally, the study contributes methodologically by employing PLS-SEM to analyze a complex model with multiple constructs, demonstrating its suitability for examining emerging and interdisciplinary research contexts. The strong explanatory and predictive power of the model further supports the robustness of the extended framework.

7.2 Managerial Implications

The findings of this study offer several practical implications for organizations, HR professionals, and decision-makers involved in AI-driven recruitment and talent management.

First, the significant impact of facilitating conditions suggests that organizations must invest in infrastructure, training, and technical support to successfully implement AI-driven recruitment systems. Without adequate organizational readiness, even advanced technologies may fail to achieve desired outcomes.

Second, the strong influence of effort expectancy highlights the importance of user-friendly AI systems. Organizations should prioritize intuitive interfaces and ease of use when adopting AI tools to ensure higher acceptance among HR professionals.

Third, the results emphasize the role of performance expectancy, indicating that organizations should clearly communicate the benefits and efficiency gains associated with AI-driven recruitment. Demonstrating tangible improvements in hiring outcomes can significantly enhance adoption intentions.

Fourth, the significance of industry demand and skill transformation underscores the need for organizations to align their recruitment strategies with evolving market requirements. HR managers must proactively identify emerging skill trends in marketing and leverage AI tools to effectively source and evaluate candidates with relevant competencies.

Additionally, the relatively weaker effect of social influence suggests that AI adoption in HR is driven more by strategic and performance-oriented considerations rather than peer pressure. Therefore, organizations should focus on building a strong business case for AI adoption rather than relying solely on normative influence.

Overall, the study provides actionable insights for organizations seeking to enhance their AI-driven talent acquisition strategies, enabling them to remain competitive in a rapidly evolving technological landscape.

8. Conclusion

This study examined the impact of artificial intelligence on evolving skill demand in marketing and its implications for AI-driven talent acquisition in human resource management using an extended UTAUT framework. The findings provide strong empirical evidence supporting the proposed model, highlighting the significant role of technological, organizational, and industry-related factors in influencing the adoption of AI-driven recruitment systems.

The results reveal that behavioral intention is a key determinant of adoption, confirming its central role in technology acceptance. Among the antecedents, facilitating conditions and effort expectancy emerged as the most influential factors, emphasizing the importance of organizational support and ease of use in driving AI adoption. Additionally, performance expectancy, industry demand, and skill transformation were found to significantly influence behavioral intention, demonstrating the relevance of both traditional UTAUT constructs and newly introduced contextual variables.

One of the key contributions of this study lies in the extension of the UTAUT model by incorporating industry demand and skill transformation, thereby providing a more comprehensive framework for understanding AI adoption in the context of workforce evolution. Furthermore, the study bridges the gap between marketing and human resource management, offering insights into how changes in skill demand influence recruitment strategies.

The findings also provide important practical insights for organizations, highlighting the need to invest in AI infrastructure, training, and user-friendly systems, while aligning recruitment strategies with evolving market demands. These insights are particularly relevant for organizations seeking to remain competitive in an

increasingly AI-driven environment.

In conclusion, this study underscores the growing importance of integrating AI into both marketing and HR functions and demonstrates that successful adoption depends not only on technological capabilities but also on organizational readiness and external market dynamics. The proposed model offers a robust foundation for future research exploring AI adoption and workforce transformation across different industries and contexts.

9. Limitations and Future Research

Limitations

Despite providing valuable insights, this study is subject to certain limitations that should be acknowledged.

First, the study is based on data collected from respondents primarily located in Tier 1 and Tier 2 cities, which may limit the generalizability of the findings to other regions, particularly rural or less technologically advanced areas. The adoption of AI technologies may vary significantly across different geographic and economic contexts.

Second, the sample consists of HR professionals and job applicants, which, although relevant to the study objectives, may not fully capture the perspectives of other stakeholders such as senior management, policymakers, or technology developers. Including a broader range of respondents could provide a more comprehensive understanding of AI adoption in organizational settings.

Third, the study adopts a cross-sectional research design, which captures responses at a single point in time. As a result, it does not account for changes in perceptions and adoption behavior over time. Given the rapid evolution of AI technologies, longitudinal studies could offer deeper insights into how adoption patterns develop and change.

Fourth, while the study extends the UTAUT model by incorporating industry demand and skill transformation, other potentially relevant factors—such as organizational culture, ethical concerns, and data privacy issues—were not included. These factors may also influence AI adoption and should be considered in future research.

9.2. Future Research Directions

Building on the limitations of this study, several avenues for future research are suggested.

First, future studies can expand the scope by including respondents from diverse geographic regions and industries, enabling a more comprehensive and generalizable understanding of AI adoption across different contexts. Second, researchers may explore industry-specific models, particularly focusing on sectors where AI adoption is rapidly evolving, such as healthcare, finance, and e-commerce. Comparative studies across industries could provide valuable insights into contextual differences in adoption behavior.

Third, future research can incorporate additional constructs such as organizational culture, trust in AI, perceived risk, and ethical considerations, which are increasingly relevant in the context of AI-driven decision-making.

Fourth, longitudinal studies can be conducted to examine how behavioral intention and adoption evolve over time, particularly as organizations gain more experience with AI technologies.

Finally, future studies may employ mixed-method approaches, combining quantitative and qualitative techniques to gain deeper insights into the underlying motivations and challenges associated with AI adoption in HR and marketing domains.

References-

- Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2023). Understanding AI adoption in organizations: A systematic review and future research agenda. *Technological Forecasting and Social Change*, 187, 122187. <https://doi.org/10.1016/j.techfore.2022.122187>
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., & Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Huang, M.-H., & Rust, R. T. (2021). Artificial intelligence in service. *Journal of Service Research*, 24(1), 3–19. <https://doi.org/10.1177/1094670520902266>
- Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. A. (2022). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, 59(2), 103444. <https://doi.org/10.1016/j.im.2020.103444>
- Upadhyay, A. K., & Khandelwal, K. (2018). Applying artificial intelligence: Implications for recruitment. *Strategic HR Review*, 17(5), 255–258. <https://doi.org/10.1108/SHR-07-2018-0051>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178. <https://doi.org/10.2307/41410412>
- Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): A literature review. *International Journal of Information Management*, 35(3), 443–458. <https://doi.org/10.1016/j.ijinfomgt.2015.02.003>
- Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 24–42. <https://doi.org/10.1007/s11747-019-00696-0>
- Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing*, 80(6), 97–121. <https://doi.org/10.1509/jm.15.0413>
- Mariani, M., Baggio, R., Fuchs, M., & Höepken, W. (2018). Business intelligence and big data in hospitality and tourism: A systematic literature review. *International Journal of Contemporary Hospitality Management*, 30(12), 3514–3554. <https://doi.org/10.1108/IJCHM-07-2017-0461>
- Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and opportunities. *Academy of Management Annals*, 13(2), 667–707. <https://doi.org/10.5465/annals.2018.0039>
- Minbaeva, D. (2021). Disruption in human resource management. *Human Resource Management Review*, 31(1), 100742. <https://doi.org/10.1016/j.hrmr.2019.100742>
- Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, 46(1), 192–210. <https://doi.org/10.5465/amr.2018.0072>
- Jarrahi, M. H. (2018). Artificial intelligence and the future of work. *Business Horizons*, 61(4), 577–586. <https://doi.org/10.1016/j.bushor.2018.03.007>
- Autor, D. H. (2015). Why are there still so many jobs? *Journal of Economic Perspectives*, 29(3), 3–30. <https://doi.org/10.1257/jep.29.3.3>

- Frey, C. B., & Osborne, M. A. (2017). The future of employment. *Technological Forecasting and Social Change*, 114, 254–280. <https://doi.org/10.1016/j.techfore.2016.08.019>
- Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance. *Journal of Business Research*, 70, 356–365. <https://doi.org/10.1016/j.jbusres.2016.08.016>
- Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making. *International Journal of Information Management*, 48, 63–71. <https://doi.org/10.1016/j.ijinfomgt.2019.01.002>
- Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand. *Business Horizons*, 62(1), 15–25. <https://doi.org/10.1016/j.bushor.2018.08.004>
- Borges, A. F. S., Laurindo, F. J. B., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in marketing. *Journal of Business Research*, 124, 439–451. <https://doi.org/10.1016/j.jbusres.2020.10.062>
- Kraus, S., Durst, S., Ferreira, J. J., Veiga, P., Kailer, N., & Weinmann, A. (2021). Digital transformation in business. *Journal of Business Research*, 123, 557–567. <https://doi.org/10.1016/j.jbusres.2020.10.042>
- Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation. *Journal of Business Research*, 122, 889–901. <https://doi.org/10.1016/j.jbusres.2019.12.022>
- Sharma, A., Sharma, T., Dwivedi, Y. K., & Al-Khalifa, K. N. (2020). Artificial intelligence adoption. *Journal of Business Research*, 120, 174–185. <https://doi.org/10.1016/j.jbusres.2019.09.055>