

Academic Journal of Research and Scientific Publishing

International, peer-reviewed scientific journal

The 79th Issue

Publication date: 05-11-2025

ISSN: 2706-6495

Doi: doi.org/10.52132/Ajrsp.e.2025.79

Email: editor@ajrsp.com

Dedication

It is our pleasure and great privilege to present the 79th issue of the Academic Journal of Research and Scientific Publishing to all researchers and professor who published their research in the issue, and we thank and appreciate to all contributors and supporters of the academic journal and those involved in the production of this scientific knowledge edifice.

Academic Journal of Research and Scientific Publishing

Editorial Board

Chief Editor:

Prof. Khetam Ahmed Al-Nagdi

Advisory Members:

Prof. Abdul Hakim Ahmed Sirr Al-Khatim Jinni

Prof. Riad Said Ali Al-Mutairi

Editorial Members:

Prof. Khaled Mohamed Abdel-Fattah Abu Shaira

Prof. Azab Alaziz Alhashemi

Prof. Khaled Ibrahim Khalil Hijazi Abu Alqumsan

Dr. Abdel Razek Wahba Sayed Ahmed

Prof. Abdel Fattah Hussein

Table of Content:

No	Paper title	Author Name	Country	Field	Page No
1	Adoption of Generative AI Technologies and Their Impact on Employee Well-being in Universities: An Empirical Study Using the Technology Acceptance Model (TAM)	Refah Nasser AL-Qahtani	Saudi Arabia	Public Administration	5-32
2	The Role of Artificial Intelligence in Transforming Human Resource Management Processes (an Analytical Study)	Norah Ahmed Almuhanha	Saudi Arabia	Human Resource Management	33-59

Adoption of Generative AI Technologies and Their Impact on Employee Well-being in Universities: An Empirical Study Using the Technology Acceptance Model (TAM)

Refah Nasser AL-Qahtani

PhD Student, Department of Public Administration, College of Business Administration, King Saud University, Saudi Arabia

Email: Refaanas92@gmail.com

Received:

25 September 2025

First Decision:

2 October 2025

Revised:

20 October 2025

Accepted:

27 October 2025

Published:

5 November 2025

Copyright © 2025

by Refah Nasser AL-Qahtani and AJRSP. This is an open-access article distributed under the terms of the Creative Commons Attribution license (CC BY NC).



Abstract

This study investigates the adoption of generative artificial intelligence (AI) technologies—such as ChatGPT and DeepSeek—and their impact on employee well-being within university settings. Drawing on the Technology Acceptance Model (TAM), the research explores how perceived usefulness, ease of use, and enjoyment influence the adoption of AI tools by administrative staff. A quantitative survey was conducted with 164 university employees using a structured questionnaire. The findings revealed that perceived enjoyment is the only statistically significant predictor of AI adoption, while perceived usefulness and ease of use did not show significant effects. Furthermore, the adoption of generative AI tools was positively associated with employee happiness and negatively associated with stress levels. These results highlight the importance of intrinsic motivation and user experience in driving technology acceptance, especially in voluntary-use contexts. The study provides practical insights for university administrators seeking to enhance both AI adoption and employee well-being. The study recommends examining external factors such as organizational support, peer influence, and corporate culture to uncover how social and environmental conditions affect AI adoption. Equally important is addressing the potential downsides of AI, including user anxiety, job insecurity, and ethical concerns.

Keywords: Generative AI, Technology Acceptance Model, Employee Well-being, ChatGPT, Higher Education, TAM

1. Introduction

The rapid advancement of generative artificial intelligence (AI) technologies has significantly reshaped organizational and educational environments worldwide. Tools such as ChatGPT, DeepSeek, Google Gemini, and Microsoft Copilot are increasingly utilized to automate routine tasks, support writing and communication, assist in data processing, and enhance efficiency in the workplace. This ongoing transformation has positioned generative AI as a key driver in digitalization strategies adopted by higher education institutions (Crompton & Burke, 2023).

Recent discussions in higher education highlight both the opportunities and challenges of integrating generative AI. While many studies emphasize its role in enhancing academic work and instructional activities, there is growing recognition that AI adoption also influences psychological and social dimensions within the work environment, particularly in relation to employee well-being. However, the majority of existing research has focused on students and faculty members, while comparatively less attention has been given to administrative and support employees, despite their crucial role in ensuring the continuity and quality of institutional operations (Crompton & Burke, 2023).

The Technology Acceptance Model (TAM) provides a useful theoretical foundation for examining workplace adoption of technological tools. Traditionally, TAM emphasizes perceived usefulness and perceived ease of use as primary predictors of adoption behavior. However, emerging empirical evidence suggests that in the context of generative AI—which is novel, interactive, and exploratory in nature—intrinsic motivational factors, such as perceived enjoyment, may play a stronger role in influencing adoption decisions (Cambra-Fierro et al., 2024). This shift highlights the need to reconsider classical TAM assumptions when studying AI adoption in contemporary settings.

Moreover, recent research indicates that generative AI use may influence employees' workplace well-being, including job satisfaction, emotional balance, and stress levels (Cambra-Fierro et al., 2024). Yet, empirical evidence remains limited regarding whether these well-being effects apply to non-academic university employees, who often face high administrative workloads, frequent communication demands, and procedural responsibilities.

Accordingly, this study seeks to address this gap by examining the adoption of generative AI among university administrative employees, focusing on the roles of perceived usefulness,

perceived ease of use, and perceived enjoyment in influencing adoption, as well as the effect of adoption on employees' happiness and stress levels. By centering on this professional group, the study contributes to a more comprehensive understanding of AI integration within higher education and provides insights for institutions aiming to support both effective adoption and employee well-being.

1.1. Research Problem

The adoption of generative AI technologies, such as ChatGPT and DeepSeek, is transforming university workplaces by automating tasks and enhancing efficiency. While prior research has extensively applied the Technology Acceptance Model (TAM) to study technology adoption (Davis, 1989; Venkatesh, 2000), most studies focus on students and educators, overlooking university employees. Additionally, while TAM highlights perceived usefulness and ease of use, the role of enjoyment in AI adoption remains underexplored (Agarwal & Karahanna, 2000; Padilla-Meléndez et al., 2013). Furthermore, existing research often assumes positive workplace outcomes without fully examining AI's psychological impact, including potential stressors such as technological complexity and job insecurity (Jeon & Lee, 2023).

A significant gap exists in understanding how AI adoption affects employee well-being in higher education institutions. Studies on workplace well-being emphasize job satisfaction and stress reduction (Xanthopoulou et al., 2012; Ryan & Deci, 2001), yet few address the specific effects of AI tools on non-academic staff. This study seeks to bridge this gap by investigating whether AI-driven efficiency leads to improved well-being or unintended stressors, contributing both to theoretical advancements in TAM and practical strategies for optimizing AI integration in university settings (Tlili et al., 2023).

2. Literature Review

Technological advancements have significantly reshaped workplace environments, including those in higher education institutions (Adams et al., 2024; Ali et al., 2024; Ansari et al., 2024; Mukul & Büyüközkan, 2023; Rawas, 2023). Universities are rapidly integrating digital tools to enhance administrative efficiency, streamline operations, and improve employee productivity. While these technologies bring numerous benefits, they also present challenges related to workforce adaptation and well-being (Adamson & Sloan, 2022). Among the most transformative technologies are generative artificial intelligence (AI) tools, which have become

increasingly prevalent across various sectors, including higher education administration.

Generative AI refers to advanced machine learning models capable of producing human-like text, images, and other forms of content based on input prompts (Lim et al., 2023). Tools such as ChatGPT, DeepSeek, Bard, and Claude have been adopted in workplace settings to assist with administrative tasks, automate routine processes, and enhance decision-making (Bhutoria, 2022; Mousavinasab et al., 2021). In higher education institutions, non-academic employees, including administrative staff, IT personnel, and support services, are increasingly using generative AI to handle inquiries, draft reports, process student applications, and manage large datasets efficiently (Korneeva et al., 2023). These AI-driven tools have the potential to reduce employees' workload, improve response times, and enhance overall operational efficiency.

Despite these advantages, the adoption of generative AI in university administration has sparked discussions on both its benefits and concerns. Some studies highlight how these tools enhance efficiency, accessibility, and user experience, allowing employees to focus on more complex and strategic tasks (Ansari et al., 2024; Lo, 2023). Generative AI can assist in document creation, meeting transcription, automated email responses, and chatbot-based student support (Li et al., 2024; Maheshwari, 2024). However, concerns related to job security, data privacy, and ethical implications have also been raised (Ali et al., 2024; Tlili et al., 2023). Employees may worry about AI replacing human roles, increasing reliance on automated decision-making, and the risks of data breaches when handling sensitive institutional information (Mucharraz & Cano, 2023). These mixed perceptions necessitate further research into how university employees interact with generative AI and how their experiences influence workplace well-being.

While the academic literature on AI in education is expanding, most studies have focused on its use in teaching and learning rather than in administrative and support functions (Adams et al., 2024; Maheshwari, 2024). Most of the existing research examines how AI tools impact students and faculty, with limited attention given to the perspectives of non-academic university employees (Bower et al., 2024; Guo & Wang, 2023; Jeon & Lee, 2023; Velandar et al., 2023). This gap is significant because administrative staff play a crucial role in maintaining institutional operations and ensuring smooth interactions between students, faculty, and university management (Bruggeman et al., 2022). Understanding how these employees perceive, adopt, and integrate AI-driven tools like ChatGPT and DeepSeek into their daily tasks is essential for evaluating both their productivity and job satisfaction.

To explore this, this study applies the Technology Acceptance Model (TAM) to assess the adoption of generative AI tools among university employees (Davis, 1989). The TAM framework is widely used to examine how perceived usefulness, ease of use, and user attitudes influence technology acceptance (Scherer et al., 2019; Wojciechowski & Vellary, 2013; Shroff et al., 2011). While TAM traditionally emphasizes the functional benefits of technology, recent studies suggest that emotional and experiential factors—such as enjoyment and stress reduction—also play a role in AI adoption (Mehta et al., 2019; Ukpabi & Karlajuoto, 2017). Generative AI tools, particularly conversational models like ChatGPT and DeepSeek, can be engaging and intuitive, potentially increasing user satisfaction and reducing the cognitive burden of repetitive administrative tasks.

Beyond adoption factors, this study also examines the impact of generative AI on employee well-being. Workplace well-being is an essential factor in modern institutions, as digital transformation influences workload management, stress levels, and overall job satisfaction (Kinman & Court, 2010; Franco-Santos & Doherty, 2017). While AI tools have the potential to reduce stress by automating mundane tasks, they can also create challenges related to job displacement fears, increased surveillance, and expectations of constant availability (Stojanov & Daniel, 2023). Previous research has primarily examined well-being among faculty members, while limited studies have analyzed how AI affects the well-being of university administrative and support employees (Caprara & Caprara, 2022). This study aims to address this gap by investigating whether the adoption of generative AI tools enhances employee happiness and energy levels while simultaneously mitigating workplace stress.

By examining these aspects, this study contributes to a deeper understanding of how university employees interact with generative AI tools and how these technologies influence their workplace experiences. The findings will offer valuable insights for higher education institutions, helping administrators develop policies that support AI adoption while ensuring a balanced and sustainable work environment.

3. Conceptual framework and hypotheses development

3.1. Technology Adoption: The TAM Framework

Technology adoption is a complex and non-uniform process, with users demonstrating diverse behaviors when engaging with new technological tools. Several theoretical models have

been developed to explain the factors that influence the adoption, sustained usage, and integration of new technologies into daily routines. Among these models, the Technology Acceptance Model (TAM) proposed by Davis (1989) is one of the most widely recognized frameworks. It has been extensively utilized in various fields, including education, to analyze technology adoption (e.g., Wojciechowski & Vellary, 2013; Shroff et al., 2011). TAM posits that perceived usefulness and perceived ease of use are the primary factors influencing users' attitudes and decisions regarding technology adoption (Davis, 1989).

Within the context of higher education institutions, TAM is particularly valuable for understanding and predicting the adoption of generative artificial intelligence (AI) tools, including ChatGPT, DeepSeek, and other AI-driven technologies. By providing insights into how university employees perceive the usefulness and ease of use of these tools, TAM helps institutions strategically implement AI-powered technologies, ensuring their seamless integration into professional practices (Scherer et al., 2019).

Additionally, TAM serves as a guiding framework for the design and execution of professional development programs, aimed at enhancing employees' technological competencies and confidence in utilizing generative AI tools (Antonietti et al., 2022). Addressing the key determinants of technology acceptance—perceived usefulness and ease of use—is essential for professional development initiatives, as these factors significantly impact employees' willingness to adopt and effectively integrate AI technologies into their professional responsibilities (Persico et al., 2014).

Recent research highlights TAM's effectiveness in explaining the adoption of e-learning technologies and digital tools within institutional settings (Al-Adwan et al., 2023; He et al., 2023; Mailizar et al., 2021; Al-Qaysi et al., 2020). These studies reinforce TAM as a robust analytical framework for assessing how employees perceive new technologies, which, in turn, influences their attitudes and intentions toward adoption. Given this empirical support, TAM enables researchers to identify the critical factors that shape technology acceptance and adoption behavior among non-academic university employees (Scherer et al., 2019).

3.2. University Employees' Well-being: The Key Role of Happiness and Stress

Our framework suggests that the adoption of generative artificial intelligence (AI) tools, including ChatGPT, DeepSeek, and similar technologies, may influence the well-being of

university employees. The concept of well-being lacks a singular definition in the literature; however, there is general agreement that workplace well-being encompasses positive emotions, job satisfaction, and a sense of purpose, while also being characterized by the absence of negative factors such as stress, anxiety, and burnout (Xanthopoulou et al., 2012; Bakker & Oerlemans, 2011; Ryan & Deci, 2001). From a broader perspective, well-being reflects the overall evaluation employees make regarding their work experiences (Xanthopoulou et al., 2012). Employees who experience job satisfaction and positive emotions are more likely to report higher well-being levels, whereas negative emotions, such as stress and frustration, tend to reduce workplace well-being (Bakker & Oerlemans, 2011).

When assessing well-being, Van de Voorde et al. (2012) emphasize the importance of considering multiple components, though they do not explicitly define them. Peccei (2004) similarly describes well-being as a balance between positive aspects (e.g., job satisfaction) and negative aspects (e.g., stress), which can affect employees' overall health. However, both Peccei (2004) and Van de Voorde et al. (2012) acknowledge limitations in their frameworks, as they do not fully account for all workplace experiences that may influence well-being. Nonetheless, their work establishes a foundation for further research, particularly regarding the interplay between positive and negative factors shaping employee well-being.

Drawing on Peccei's (2004) approach, happiness-related well-being can be defined as employees' subjective experiences of satisfaction and commitment at work. Happiness is often described as an internal state of fulfillment and emotional harmony that influences employees' relationships with their work environment (Lu, 2001). In contrast, health-related well-being is primarily impacted by stressors such as workload, job strain, and burnout, as well as employees' coping mechanisms. Stress arises when external pressures exceed an individual's ability to manage them effectively, leading to tension and anxiety (Szabó & Lovibond, 2006).

Finally, Peccei (2004) also introduces the concept of relationship well-being, which encompasses interactions among employees, supervisors, and the broader organizational environment. However, given that our research focuses solely on individual AI adoption, we specifically examine happiness and health-related well-being (with stress as the negative component) as the primary factors in our empirical study. Accordingly, as illustrated in Figure 1, our causal model establishes a link between technology adoption and the well-being perceptions of university employees.

3.3. Hypotheses Development

From a conceptual perspective, this study builds on the Technology Acceptance Model (TAM), which serves as the foundation for understanding the factors that drive generative AI adoption among university employees.

One of the core components of TAM is **perceived usefulness**, which refers to the extent to which an individual believes that using a particular technology enhances their overall performance (Davis et al., 1989). Several studies have explored how perceived usefulness influences technology adoption in educational and workplace settings (Ansari et al., 2024; Xiao et al., 2023; Shen et al., 2022; Mehta et al., 2019; Padilla-Meléndez et al., 2013). Based on prior research, individuals who perceive a new AI tool as beneficial for improving their work efficiency and performance are more likely to engage with and adopt it. Therefore, we propose the following hypothesis:

Hypothesis 1: *There is no significant relationship between employees' perceived usefulness of generative AI and their adoption of it.*

Another key determinant in technology adoption is **perceived ease of use**, which refers to how simple and effortless a user finds a given technology (Venkatesh, 2000). This factor plays a crucial role in reducing barriers to adoption, accelerating the learning curve, and enhancing user proficiency (Xiao et al., 2023; Sheppard & Vibert, 2019). Technologies that require minimal effort to learn and integrate into daily routines tend to have higher adoption rates. In this context, generative AI tools, such as ChatGPT and DeepSeek, must be perceived as easy to use to encourage university employees to adopt them. Based on this, we propose:

Hypothesis 2: *There is no significant relationship between employees' perceived ease of use of generative AI and their adoption of it.*

While TAM traditionally emphasizes usefulness and ease of use, scholars have argued that these dimensions alone may not fully explain technology adoption (Mehta et al., 2019; Ukpabi & Karjaluoto, 2017). Thus, researchers suggest incorporating additional variables, such as enjoyment, which can play a key role in the adoption process, particularly in contexts characterized by technological uncertainty (Agarwal & Karahanna, 2000). Enjoyment is defined as the pleasure and satisfaction derived from using a technology, and it has been shown to contribute to sustained usage and long-term engagement (Fang & Zhao, 2010; Moon & Kim,

2001; Lin et al., 2020; Barak et al., 2016; Padilla-Meléndez et al., 2013). When employees find a tool enjoyable, their likelihood of adopting and continuously using it increases. Therefore, we propose:

Hypothesis 3: *There is no significant relationship between employees' perceived enjoyment of generative AI and their adoption of it.*

Beyond adoption, it is also critical to examine how generative AI impacts employee well-being. Well-being is broadly defined as a balance between positive emotions (e.g., happiness) and negative feelings (e.g., stress), both of which can influence employees' health and productivity (Peccei, 2004; Xanthopoulou et al., 2012; Ryan & Deci, 2001). Happiness is often described as an internal state of satisfaction and fulfillment, linked to positive workplace experiences (Lu, 2001). On the other hand, stress arises when external demands exceed an individual's ability to cope, leading to tension and anxiety (Szabó & Lovibond, 2006).

In the context of generative AI adoption, previous research suggests that AI tools can enhance productivity and reduce workload, ultimately promoting a healthier work-life balance (Jeon & Lee, 2023; Tlili et al., 2023). When used effectively, AI technologies streamline tasks, minimize administrative burdens, and improve efficiency, contributing to higher happiness levels. Conversely, if employees perceive AI as challenging or overwhelming, it may lead to increased stress.

Therefore, we put forth our final hypothesis:

Hypothesis 4: *The adoption of generative AI has no significant impact on employee well-being in terms of (a)happiness and (b)stress reduction.*

4. Methodology:

4.1 Research Design:

This study adopted a quantitative research design to explore how generative AI tools—such as ChatGPT and DeepSeek—affect the well-being of university employees. It relied on the Technology Acceptance Model (TAM) as the conceptual framework to examine adoption behaviors (Davis, 1989; Venkatesh & Davis, 2000).

Data were collected through an online survey, which enabled systematic analysis of variables including Perceived Usefulness (PU), Perceived Ease of Use (PEU), and employee well-being.

The survey also included demographic information and additional constructs such as Perceived Enjoyment (ENJ), happiness, and stress.

To ensure representativeness, the study employed a simple random sampling method, giving every university employee in the population an equal chance of selection (Creswell & Creswell, 2018). This approach minimized selection bias and enhanced the generalizability of the findings.

The data were analyzed using SPSS software, applying descriptive statistics, Pearson correlation, and regression analysis to test the research hypotheses. This methodology provided reliable and generalizable insights into AI adoption trends in academic environments.

4.2 Sample Size and Justification:

Given the quantitative nature of this study and the available timeframe, a simple random sampling approach was employed. The survey was distributed to administrative employees working at a public university in Saudi Arabia between April and May 2025, and a total of 164 valid responses were obtained. This sample size exceeded the minimum recommended number based on the rule of thumb suggested by Green (1991), which states that the required sample size for regression analysis should be greater than $(n > 50 + 8m)$, where (m) represents the number of independent variables. Since this study included three independent variables, the minimum sample size required was $(50 + 8 \times 3 = 74)$ participants, meaning the collected sample of 164 responses was sufficient.

This sample size was appropriate for conducting statistical analyses such as correlation and regression, as prior research recommends a minimum of 50 participants to maintain adequate statistical power in regression analysis (Green, 1991; Hair et al., 2019). Moreover, the use of simple random sampling ensured that each administrative employee had an equal chance of participation, reducing selection bias and enhancing the generalizability of the findings (Creswell & Creswell, 2018). Therefore, the final sample size provided reliable and valid insights into generative AI adoption and its impact on employee well-being, balancing methodological rigor and practical feasibility.

4.3. Data Collection Instrument:

To ensure efficient and accessible data collection, the survey was conducted online using Google Forms. This approach allowed participants to complete the survey at their convenience, reducing time constraints and enhancing response rates (Regmi et al., 2016). Additionally,

Google Forms facilitated data organization and integration with statistical analysis tools, streamlining the research process (De Bruijne & Wijnant, 2014).

The survey was structured into six sections, each designed to measure key research variables related to the adoption of generative AI tools, including ChatGPT, DeepSeek, Google Gemini, Microsoft Copilot, and others, and their impact on employee well-being. The structured questionnaire assessed employees' perceptions and experiences with these AI tools based on the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh & Davis, 2000).

The first section of the survey collected general demographic information, including participants' age groups and their most frequently used generative AI tool in their work environment. This information provided a basis for analyzing AI adoption trends across different age groups and AI tool preferences.

The second section measured Perceived Usefulness (PU), assessing whether generative AI tools enhanced productivity and reduced the time required to complete tasks. Participants rated statements regarding how these technologies streamlined work processes and improved efficiency.

The third section evaluated Perceived Ease of Use (PEU), determining whether employees found generative AI tools intuitive and easy to learn. It included items exploring whether participants required extensive training to use AI tools effectively.

The fourth section assessed Perceived Enjoyment (ENJ), measuring the level of engagement and satisfaction employees experienced while using generative AI tools. It examined whether these technologies made tasks more interactive and enjoyable, contributing to higher motivation.

The fifth section focused on Adoption Intention (AI), investigating employees' willingness to continue using AI tools in the future and their likelihood of recommending them to colleagues.

The final section examined Employee Well-being (WB), focusing on two key aspects: happiness and stress. Participants indicated whether generative AI tools contributed to increased workplace happiness or reduced stress levels.

All survey items were measured using a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), ensuring consistent and systematic data collection. By utilizing Google Forms, responses were automatically recorded, allowing for seamless data processing and integration with SPSS for statistical analysis. This method ensured accuracy, efficiency, and accessibility for participants, facilitating a structured and reliable data collection process.

A total of 164 university employees participated in the survey, providing a robust dataset for statistical analysis and ensuring sufficient statistical power for hypothesis testing.

4.4. Data Analysis:

The collected data were analyzed using SPSS software to ensure accuracy, reliability, and meaningful interpretation of findings. The analysis began with descriptive statistics, summarizing means, standard deviations, and frequency distributions of the key variables, providing an overview of the dataset (Field, 2018). This was followed by Pearson's correlation analysis, which examined the strength and direction of relationships between Perceived Usefulness (PU), Perceived Ease of Use (PEU), Perceived Enjoyment (ENJ), AI adoption, and Employee Well-being (WB) (Davis, 1989).

To further assess the causal relationships between technology adoption and employee well-being, regression analysis was conducted to determine the impact of AI adoption on happiness and stress. Before proceeding with the statistical analyses, the dataset was carefully screened for missing values and outliers to maintain data integrity. Additionally, Cronbach's alpha was used to assess the internal consistency and reliability of the survey items (Taber, 2018).

Once the data met validity and reliability criteria, correlation and regression analyses were applied to test the study's hypotheses and derive insights into the factors influencing AI adoption and its effects on employee well-being.

4.5. Ethical Considerations

To ensure the ethical integrity of this research, several measures were implemented to protect participants' rights and maintain research credibility. Prior to survey completion, all participants received clear and detailed information about the study's purpose, ensuring they fully understood their involvement and provide informed consent voluntarily (Resnik, 2018). Participation was completely anonymous and confidential, as no personally identifiable information was collected, thereby ensuring privacy protection and data security in compliance with ethical research standards (Saunders et al., 2015).

Furthermore, participation in this study was entirely voluntary, allowing employees to withdraw at any stage without facing any consequences or penalties. This ensured that all responses are provided freely and without coercion, thereby minimizing the risk of psychological distress or undue pressure. To maintain transparency, all ethical procedures were aligned with

the principles outlined in the Belmont Report and institutional review board (IRB) guidelines (U.S. Department of Health & Human Services, 2018). By adhering to these ethical standards, this study was upholding research integrity while safeguarding the rights, autonomy, and well-being of all participants.

5. Findings:

5.1 Descriptive analysis

The primary data has been collected by distributing an electronic questionnaire to possible respondents of the research sample.

- Age range of the respondents:

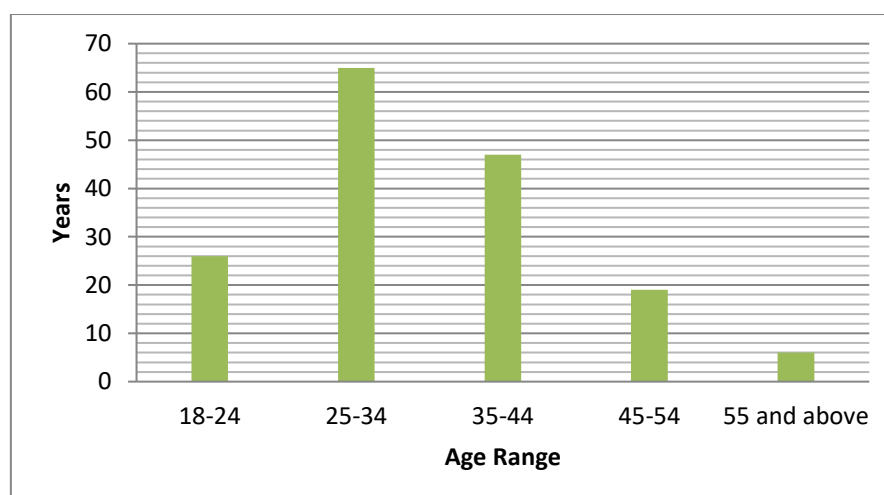
According to the table (1), the age range of the respondents is as follows:

Table (1): Age range of the respondents

Age Range	Frequency	Percentage
18-24	26	16.00%
25-34	65	39.90%
35-44	47	28.80%
45-54	19	11.70%
55 and above	6	3.70%
Total	163	100.00%

The age range of the respondents can also be illustrated as in the following figure:

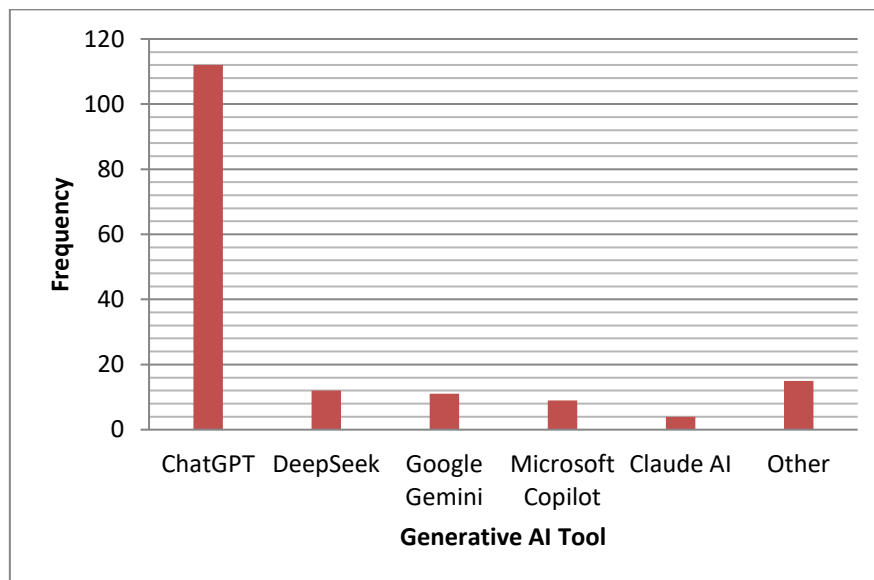
Figure (1): Age range of the respondents



- Type of AI Tool Used

Table (2): Type of Generative AI Tool Used by Respondents

Generative AI Tool	Frequency	Percentage
ChatGPT	112	68.70%
DeepSeek	12	7.40%
Google Gemini	11	6.70%
Microsoft Copilot	9	5.50%
Claude AI	4	2.50%
Other	15	9.20%
Total	163	100.00%

Figure (2): Type of Generative AI Tool Used by Respondents**Table (3):** Cross-Tabulation Between Age Range and Type of AI Tool Used

Type of AI Tool	Age Range					Total
	18-24	25-34	35-44	45-54	55 and above	
ChatGPT	25	36	33	13	5	112
DeepSeek	0	7	5	0	0	12
Google Gemini	0	5	4	2	0	11

Microsoft Copilot	0	3	3	2	1	9
Claude AI	0	3	0	1	0	4
Other	1	11	2	1	0	15
Total	26	65	47	19	6	163

5.2. Mean and Standard Deviation of the variables

This part of the data analysis involves central tendency and the dispersion, i.e. the mean, standard deviation and the range of the six variables of the research.

Table (4): Mean and Standard Deviation of the variables

Variables	Mean	Standard Deviation
Usefulness	4.08	0.82
Easiness	3.70	0.85
Enjoyment	3.97	0.83
Adoption	4.16	0.78
Happiness	3.90	0.88
Stress Reduction	3.83	0.94

To specify the minimum and the maximum length of the 5-point Likert type scale used in the questionnaire of this research, the range is calculated by $(5 - 1 = 4)$ then divided by five as it is the greatest value of the scale ($4 \div 5 = 0.80$). Then, number one which is the least value in the scale is added in order to identify the maximum of the first grade. Therefore, the length of each grade is determined below:

- From 1 to 1.80 represents (strongly disagree).
- From 1.81 until 2.60 represents (disagree).
- From 2.61 until 3.40 represents (neutral).
- From 3.41 until 4.20 represents (agree).
- From 4.21 until 5.00 represents (strongly agree).

Therefore, the grades of the six variables of the research are displayed as in the following tables:

Table (5): Grades of the six variables of the research

Variables	Mean	Grade
Usefulness	4.08	Agree
Easiness	3.70	Agree
Enjoyment	3.97	Agree
Adoption	4.16	Agree
Happiness	3.90	Agree
Stress Reduction	3.83	Agree

5.3. The Reliability Analysis:

The reliability of a measure can be analyzed by testing for both consistency and stability. Consistency indicates how well the items measuring a concept hang together as a set. Cronbach's alpha is a reliability coefficient that indicates how well the items in a set are positively correlated to one another (Sekaran & Bougie, 2010). The generally agreed upon limit for Cronbach's alpha is 0.70, although, it may decrease to 0.60 (Hair et al., 2014).

Cronbach's alpha of all variables in this research is 0.857, which is very high and assures the consistency of the measures used to explain the variables of this research. Furthermore, the high value of Cronbach's alpha of the variables of this research is not mainly attributed to a single variable rather the others because the value of Cronbach's alpha is still high even if any of the six variables of this research has been deleted.

Table (6) shows the values of Cronbach's alpha when any of the 6 variables is deleted:

Table (6): Cronbach's Alpha values if any of the research variables is deleted

The variable	Cronbach's Alpha if Item Deleted
Usefulness	0.820
Easiness	0.846
Enjoyment	0.812
Adoption	0.849
Happiness	0.822
Stress Reduction	0.847

On the other hand, the other perspective of reliability (which is stability) is also considered. Hair et al. (2014), state that stability is primarily dependent on the sample size and the number of cases per variable. The sample size of this research is 163 individuals, and the number of variables is six. Thus, the ratio of variables to cases is 1:27, which is higher than the recommended ratio of 1:20. ratio.

5.4. The Validity Analysis

Hair et al. (2014), specify that the content validity, which is also known as face validity, subjectively measures the correspondence between the individual items and the concept. In other words, Sekaran and Bougie (2010), clarified that content validity ensures that the measure includes an adequate and representative set of items that tap the concept. Whereas Kumar (2011) argued that content validity can be considered if the items are evaluated by a group of expert judges. He adds that the judgment is a tool to measure what it is supposed to be mainly based upon the logical link between the questions and the objectives of the research.

Accordingly, the researcher has received the approval from the supervisor after reviewing the research proposal which includes the questionnaire statements that are expressing the variables of this research.

5.5. Pearson Correlation between the Research Variables

Table (7) shows the correlation matrix of the research variables. Note that the correlation between any variable and itself is one.

Table (7): Pearson Correlation between the Research Variables

	Usefulness	Easiness	Enjoyment	Adoption	Happiness	Stress
Usefulness	1					
Easiness	.567**	1				
Enjoyment	.646**	.523**	1			
Adoption	.473**	.387**	.614**	1		
Happiness	.555**	.419**	.619**	.464**	1	
Stress	.502**	.388**	.492**	.267**	.621**	1

** . Correlation is significant at the 0.01 level (2-tailed).

As all values of the correlation between each pair of variables are equal or less than 0.9, table (7) validates that the correlations between the variables of the research are not high, i.e., each variable measures a different concept.

5.6. Regression Analysis:

Having the conducting and assuring conformity of reliability and validity tests, the researcher implemented multiple regressing technique to investigate the proposed relationships between independent variables (usefulness, ease of use, and enjoyment) on one side and the dependent variable (generative AI adoption) on the other side.

The summary of the multiple regression model indicates that the correlation of the independent variables (R) equals 0.624, as shown in table (8), as follows:

Table (8): Multiple Regression Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.624	0.389	0.378	0.61758

Thus, R Square is 0.389, which represents the explained variance. This result means that 38.9 % of the variance in generative AI adoption has been explained -according to Sekaran and Bougie (2010)- by the independent variables (usefulness, ease of use, and enjoyment).

To test the hypnotized relationships between the independent variables (usefulness, ease of use, and enjoyment) on one side and the dependent variable (generative AI adoption) on the other side, the researcher performed the multiple regression analysis, which resulted the coefficients illustrated in following table:

Table (9): Coefficients of the Multiple Regression

Variables	B	Std. Error	Beta	t	Sig. (p)
Usefulness	0.105	0.083	0.110	1.266	0.207
Easiness	0.051	0.071	0.056	0.718	0.474
Enjoyment	0.485	0.079	0.514	6.127	0.000

The Dependent Variable: generative AI adoption

Sekaran and Bougie (2010) indicated that in the hypotheses testing by the regression analysis, there are two evidence to decide whether reject (accept) the research hypotheses; the t-value and the p-value. Based on the degree of freedom ($n-1 = 162$) and the significance level (95%), the t-value has to be greater than or equal to 1.98 to accept the research hypothesis. On the other hand,

the p-value must be equal to or smaller than 0.05 in order to not reject the null hypothesis.

Consequently, the t-value of usefulness variable is 1.266 (which is lower than 1.98) and the p-value is 0.207 (which is higher than 0.05), and thus, both results are not supporting the hypothesis that usefulness has a positive and statistically significant influence on generative AI adoption.

Likewise, the t-value of ease-of-use variable is 0.718 (which is lower than 1.98) and the p-value is 0.474 (which is higher than 0.05), and thus, both results are not supporting the hypothesis that ease of use has a positive and statistically significant influence on the generative AI adoption.

However, the t-value of enjoyment variable is 6.127 (which is higher than 1.98) and the p-value is 0.000 (which is lower than 0.05), and thus, both results are supporting the hypothesis that ease of use has a positive and statistically significant influence on the generative AI adoption.

In addition to the multiple regression, the researcher conducted simple regression analysis to test H4ab concerning the influence of generative AI adoption on happiness and reduction of stress sequentially.

The results of the simple regression are displayed in the following tables:

Table (10): Coefficients of the Simple Regression

Variables	B	Std. Error	Beta	t	Sig. (p)
generative AI adoption	.524	.079	.464	6.650	.000

The Dependent Variable: Happiness

Table (11): Coefficients of the Simple Regression

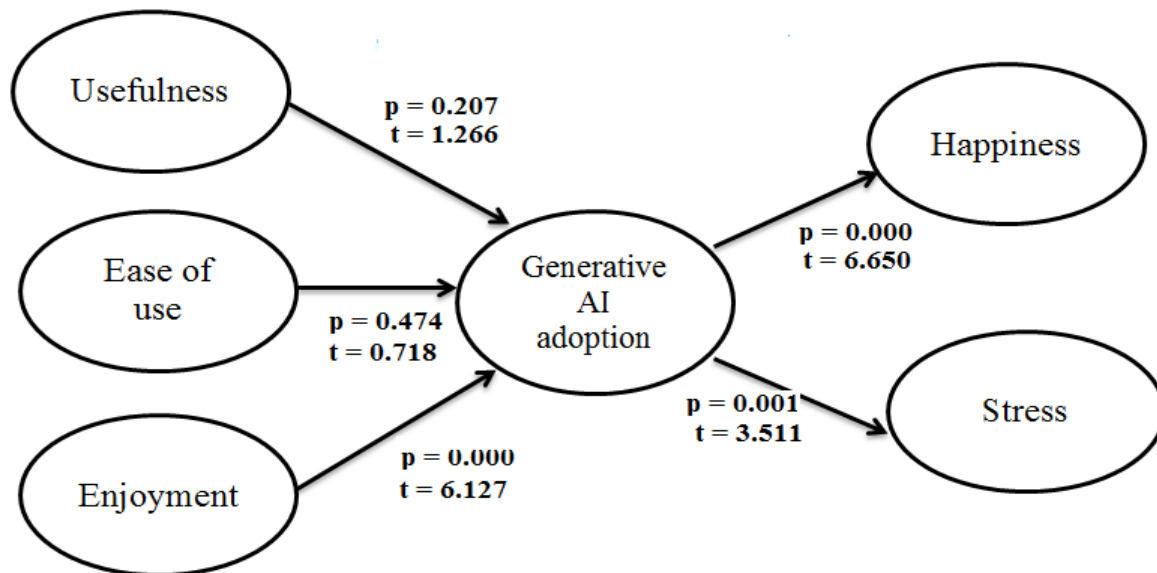
Variables	B	Std. Error	Beta	t	Sig. (p)
generative AI adoption	0.320	0.091	0.267	3.511	0.001

The Dependent Variable: Reduction of stress.

Both table (10) and table (11) show that the t-values of generative AI adoption variable are higher than 1.98, and the p-values (0.000 and 0.001) are lower than 0.05, and thus, these results are supporting the hypothesis that generative AI adoption has a positive influence a. on happiness and b. a negative influence on stress

Based on the above analyses, the results of both regression techniques are displayed as in the following diagram:

Figure (3): The Results of Regression Techniques



therefore, the decisions regarding the research hypotheses are summarized as follows:

Table (12): Summary of decisions regarding the influence of both employee's awareness and financial departments concern on the applying of governance principles

No.	The hypothesis	The decision
1	Realized usefulness of employees has a positive influence on Generative AI adoption.	Not support
2	Realized ease of use of employees has a positive influence on Generative AI Generative AI adoption.	Not support
3	Realized enjoyment of employees has a positive influence on Generative AI adoption.	Support
4a	Generative AI adoption influences employee's well-being, by having a positive impact on happiness	Support
4b	Generative AI adoption influences employee's well-being, by having a positive impact on a negative impact on stress.	Support

6. Discussion:

The findings of this study offer nuanced insights into the drivers of generative AI adoption among university employees. Most notably, perceived enjoyment emerged as the sole statistically significant predictor of employees' intention to adopt generative AI tools, whereas the traditional TAM factors – perceived usefulness and perceived ease of use – did not show significant effects. In other words, employees were more influenced by how enjoyable or intrinsically rewarding they found tools like ChatGPT or DeepSeek, rather than by judgments of practical utility or ease. This result initially seems to diverge from the classic Technology Acceptance Model, which posits perceived usefulness as a primary motivator of technology adoption (Davis, 1989).

However, our outcome aligns with emerging perspectives in technology adoption research that emphasize intrinsic motivation. For instance, Davis et al. (1992) extended TAM by incorporating perceived enjoyment as an intrinsic motivator and demonstrated that enjoyment can significantly influence usage intentions alongside usefulness (Garrity, O'Donnell, Kim, & Sanders, 2007). Similarly, van der Heijden (2004) argued that for systems with a hedonic or experiential component, perceived usefulness may lose its dominant predictive power, giving way to enjoyment as the key driver of usage (Liu & Li, 2011). Our empirical evidence strongly echoes this point: in the context of generative AI, which many users approach with curiosity and a sense of novelty, the fun or fascination derived from the technology appears to outweigh purely utilitarian considerations.

This also helps explain why perceived usefulness did not significantly influence adoption in this study. Generative AI remains relatively new in administrative workflows, meaning many employees have not yet developed clear expectations about its performance benefits. As recent research indicates, perceived usefulness tends to emerge only after users gain repeated and meaningful experience with a tool (Parveen et al., 2024). In early exploratory phases—where experimentation occurs before tangible performance gains are felt—usefulness is unlikely to drive adoption decisions. Therefore, the non-significant effect of usefulness is not a contradiction to TAM, but rather a reflection of the temporal stage at which adoption is occurring.

There are several plausible explanations for why enjoyment was the only significant predictor in this study. First, generative AI tools in the workplace occupy a somewhat dual role – they can improve productivity, but they are also innovative and exploratory in nature. Many university

staff may not yet fully recognize concrete performance benefits (“usefulness”) of tools like ChatGPT in their specific administrative or support tasks, especially since such tools are new and their best use cases are still evolving. Absent a clear immediate payoff, employees’ decisions to try or continue using the AI may hinge more on whether the experience is engaging and gratifying. In our sample, even if an employee wasn’t convinced that a generative AI tool would markedly improve their job performance, they might still experiment with it out of intrinsic enjoyment or curiosity. This behavior is consistent with intrinsic motivation theory – people tend to engage in activities that are inherently interesting or enjoyable, even lacking external incentives. By contrast, if a tool is not enjoyable, employees presumably had little motivation to incorporate it into their routines, regardless of any touted benefits. This pattern aligns with prior TAM-based studies in hedonic contexts: for example, research on online learning platforms (e.g., Lee, Cheung & Chen, 2005) and web systems (e.g., van der Heijden, 2004) has found that when users “have fun” using a system, their likelihood of adopting and continuing to use it increases significantly. Our study extends this notion to the AI-in-the-workplace context.

Moreover, the lack of a significant effect for perceived ease of use can be understood based on how generative AI tools are actually used in practice. Although these tools appear simple and user-friendly on the surface due to their conversational interfaces, using them effectively requires additional cognitive effort. Employees need to know how to phrase prompts correctly, evaluate the quality and accuracy of the generated responses, and refine or repeat the input when necessary. Therefore, many employees may perceive the tools as easy to access, but not necessarily easy to use well. As a result, even if the system itself is not difficult to operate, ease of use alone is not enough to motivate adoption unless the employee is already interested and willing to invest time in learning how to make the tool truly beneficial (Parveen et al., 2024; Soulami et al., 2024).

Second, the lack of a significant effect for perceived ease of use suggests that usability was not a distinguishing factor for these participants – possibly because generative AI interfaces (e.g., chatbots with natural language input) are generally user-friendly or because employees who were inclined to use AI were willing to overcome minor usability issues if they found the tool enjoyable. It may also indicate a ceiling effect: if most respondents found the tools reasonably easy to use, then variability in ease-of-use perceptions was low and thus less able to explain differences in adoption.

Our findings, therefore, do not contradict TAM but rather highlight how the relative influence of TAM constructs can shift in novel, voluntary-use contexts – intrinsic enjoyment can trump extrinsic utility when employees are deciding whether to embrace a cutting-edge tool that is not yet mandated or fully integrated into their workflow. In fact, this outcome is in line with the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), an extension of TAM, which explicitly includes hedonic motivation (akin to enjoyment) as a direct determinant of technology acceptance (Venkatesh et al., 2012). The present study's results validate that notion in the domain of generative AI: enjoyment (a hedonic factor) was paramount, whereas usefulness and ease of use (traditionally utilitarian factors) were insufficient to spur adoption on their own.

In addition to adoption drivers, our study explored the impact of generative AI usage on employee well-being. Here, the regression results were clear and encouraging – generative AI adoption had a statistically significant positive association with employees' self-reported happiness (job satisfaction) and a significant negative association with perceived stress. In practical terms, employees who adopted and used generative AI tools tended to report higher levels of work-related happiness and energy, and lower levels of stress, compared to those who did not. This finding provides empirical support to the notion that thoughtfully integrating AI tools can enhance certain aspects of employee well-being. One interpretation is that generative AI systems offload mundane or tedious tasks (for example, drafting routine emails or generating initial versions of reports), thereby freeing employees to focus on more meaningful or enjoyable aspects of their job – this aligns with reports that AI can enable staff to shift from monotonous tasks to more strategic, fulfilling work (Soulami et al., 2024). Consequently, users experience less strain and more satisfaction. Indeed, a recent study on faculty in higher education similarly found that adopting ChatGPT not only improved their performance but also boosted positive affect (happiness/energy) and reduced stress levels (Cambra-Fierro et al., 2024).

Our results extend that evidence to non-academic university employees. It is worth noting that while our data suggest a causal direction (AI use leads to better well-being), the cross-sectional nature of the study warrants caution: it is also conceivable that employees who are less stressed or more enthusiastic might be more inclined to try new technologies. Future longitudinal research should examine these dynamics over time. Nonetheless, considering existing literature which warns that AI's impact on work is double-edged – offering both stress relief and potential stressors (Soulami et al., 2024). Our findings provide a hopeful indication that, at least in our

context, the positive effects on well-being prevailed when employees chose to adopt generative AI. We interpret this as evidence that when AI tools are voluntarily adopted out of interest (enjoyment) rather than imposed, they are more likely to be used in ways that enhance job satisfaction (e.g., by augmenting employees' capabilities and reducing drudgery) and less likely to be seen as threatening or burdensome. Of course, this balance could shift if external pressures to use AI increased; thus, organizations must carefully manage AI integration to sustain these well-being benefits.

Finally, it is important to contextualize the above results within the unique sample of this study – namely, university administrative and support staff. Unlike faculty members or students, these employees typically operate in roles where technology adoption is not primarily driven by pedagogical necessity or curriculum requirements. Their use of generative AI is largely self-directed and supplemental to their existing processes. This context likely amplifies the role of intrinsic motivation: if an administrative staff member experiments with an AI tool, it is largely by choice and personal interest (hence enjoyment becomes decisive), whereas a professor or student might adopt AI partly due to academic trends or performance gains (hence usefulness might play a bigger role). This contextual difference is reflected in the contrast between our findings and some faculty-focused studies – for example, one study found that among university professors, perceived usefulness, ease of use, and enjoyment all positively influenced ChatGPT adoption (Cambra-Fierro et al., 2024). Our staff-focused results suggest that when the clear academic usefulness is less pronounced, enjoyment alone can drive adoption. In summary, the discussion highlights that intrinsic enjoyment is a critical lever for generative AI adoption among university employees, and that such adoption, when it occurs, is associated with improved well-being (higher job satisfaction and lower stress).

7. Conclusions and Future Research:

In conclusion, this study investigated the adoption of generative AI technologies by university employees through the lens of the Technology Acceptance Model, and examined how such adoption relates to employee well-being. Our results demonstrated that *perceived enjoyment* is the decisive factor driving employees' willingness to adopt generative AI tools, outweighing traditional considerations of usefulness and ease of use. This highlights the importance of intrinsic motivation in the acceptance of innovative technologies in the workplace. We also found that employees who adopted generative AI experienced higher job happiness and lower

stress, suggesting that, under supportive conditions, AI integration can serve as a boon to employee well-being. These findings contribute to a more nuanced understanding of technology acceptance in higher education settings, especially by shedding light on non-academic staff behavior, and underscore a largely positive narrative: when adoption is motivated by genuine enthusiasm, it can lead to improvements not just in work processes but also in how employees feel at work.

Future research on the adoption of generative AI in the workplace should explore a range of directions to deepen our understanding of its impact. Longitudinal and experimental studies are particularly needed to track how employees' attitudes and well-being evolve over time with continued AI use. These studies could clarify whether initial enjoyment remains a primary driver or if perceived usefulness and ease of use become more prominent with experience. Expanding the theoretical lens beyond traditional models is also valuable—particularly by integrating frameworks such as Self-Determination Theory, which highlights the role of autonomy, competence, and relatedness in motivating behavior.

Furthermore, external factors such as organizational support, peer influence, and institutional culture should be examined to uncover how social and environmental conditions affect adoption. It is equally important to address the potential downsides of AI, including user anxiety, job insecurity, and ethical concerns, as these may shape how AI is perceived and used. Researchers should also investigate how AI affects specific aspects of well-being, such as burnout, emotional exhaustion, and a sense of accomplishment. Qualitative methods like interviews and focus groups could offer rich insights into the lived experiences of employees using AI. Additionally, analyzing AI adoption by task type may reveal that employees view AI as highly useful for some functions and less so for others, which could refine implementation strategies.

Finally, comparative studies across stakeholder groups—such as students, faculty, and administrative staff—could identify differing patterns of acceptance, highlighting the importance of context-specific engagement strategies. Overall, future research should strive to ensure that AI integration is guided by both technological feasibility and human-centered values, fostering environments where innovation and well-being grow in tandem.

8. References:

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly*, 24(4), 665–694.

- Ansari, M., Xiao, H., Shen, Y., Mehta, K., & Padilla-Meléndez, A. (2024). Understanding technology adoption in the workplace: A TAM-based approach. *Journal of Workplace Learning*, 36(1), 55–75.
- Bakker, A. B., & Oerlemans, W. (2011). Subjective well-being in organizations. In K. S. Cameron & G. M. Spreitzer (Eds.), *The Oxford handbook of positive organizational scholarship* (pp. 178–189). Oxford University Press.
- Barak, A., Hen, L., Boniel-Nissim, M., & Shapira, N. (2016). A comprehensive review and a meta-analysis of the effectiveness of internet-based psychotherapeutic interventions. *Journal of Technology in Human Services*, 34(1), 1–30.
- Cambra-Fierro, J. J., Fuentes Blasco, M., López-Pérez, M.-E., & Trifu, A. (2024). ChatGPT adoption and its influence on faculty well-being: An empirical research in higher education. *Education and Information Technologies*. <https://doi.org/10.1007/s10639-024-12871-0>
- Crompton, H., & Burke, D. (2023). *Artificial intelligence in higher education: The state of the field*. *International Journal of Educational Technology in Higher Education*, 20(1).
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35(8), 982–1003.
- Fang, X., & Zhao, F. (2010). Personality and enjoyment of computer game play: The role of individual differences in the adoption of new technology. *Cyberpsychology, Behavior, and Social Networking*, 13(6), 587–590.
- Garrity, E. J., O'Donnell, J. B., Kim, Y. J., & Sanders, G. L. (2007). An extrinsic and intrinsic motivation-based model for measuring consumer shopping oriented Web site success. *Journal of Computer Information Systems*, 48(1), 18–30.
- Jeon, H., & Lee, S. (2023). Artificial intelligence in higher education: Impact on productivity and well-being. *Educational Technology Research and Development*, 71(2), 305–322.
- Kim, Y., Blazquez, V., & Oh, T. (2024). Determinants of generative AI system adoption and usage behavior in Korean companies: Applying the UTAUT model. *Behavioral Sciences (Basel)*, 14(11), 1035. <https://doi.org/10.3390/bs14111035>

- Lee, M. K. O., Cheung, C. M. K., & Chen, Z. (2005). Acceptance of Internet-based learning medium: The role of extrinsic and intrinsic motivation. *Information & Management*, 42(8), 1095–1104.
- Lin, X., Featherman, M., Sarker, S., & Nevo, S. (2020). Understanding online community user participation: A technology acceptance perspective. *Journal of Computer-Mediated Communication*, 25(1), 28–44.
- Liu, Y., & Li, H. (2011). Exploring the impact of use context on mobile hedonic services adoption: An empirical study on mobile gaming in China. *Computers in Human Behavior*, 27(2), 890–898.
- Lu, L. (2001). Understanding happiness: A look into the Chinese folk psychology. *Journal of Happiness Studies*, 2(4), 407–432.
- Mehta, K., Ansari, M., & Xiao, H. (2019). Expanding TAM: A critical review of technology adoption frameworks. *International Journal of Technology and Human Interaction*, 15(3), 10–25.
- Padilla-Meléndez, A., Garrido-Moreno, A., & Del Aguila-Obra, A. R. (2013). Perceived playfulness, gender differences and technology acceptance model in a blended learning scenario. *Computers & Education*, 63, 306–317.
- Parveen, K., Sharma, S., Umrao, L., & Qureshi, T. (2024). Unraveling the dynamics of ChatGPT adoption and usage in higher education. *Scientific Reports*, 14, Article 74406. <https://doi.org/10.1038/s41598-024-74406-4>
- Peccei, R. (2004). Human resource management and the search for the happy workplace. *European Journal of Industrial Relations*, 10(1), 29–53.
- Ryan, R. M., & Deci, E. L. (2001). On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. *Annual Review of Psychology*, 52, 141–166.
- Sheppard, B. H., & Vibert, C. (2019). Predicting technology adoption: An empirical comparison of TAM and other models. *Information & Management*, 56(4), 567–579.
- Soulami, M., Benchekroun, S., & Galiulina, A. (2024). Exploring how AI adoption in the workplace affects employees: A bibliometric and systematic review. *Frontiers in Artificial Intelligence*, 7, Article 1473872. <https://doi.org/10.3389/frai.2024.1473872>

- Soulami, M., Benchekroun, S., & Galiulina, A. (2024). Exploring how AI adoption in the workplace affects employees: A bibliometric and systematic review. *Frontiers in Artificial Intelligence*, 7, 1473872. <https://doi.org/10.3389/frai.2024.1473872>
- Szabó, M., & Lovibond, P. F. (2006). Anxiety, depression, and tension/stress: Their interrelations and implications for treatment. *Journal of Cognitive Psychotherapy*, 20(2), 147–159.
- Van de Voorde, K., Paauwe, J., & Van Veldhoven, M. (2012). Employee well-being and the HRM–organizational performance relationship: A review of quantitative studies. *International Journal of Management Reviews*, 14(4), 391–407.
- van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly*, 28(4), 695–704.
- Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research*, 11(4), 342–365.
- Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2012). The role of personal resources in the job demands-resources model. *International Journal of Stress Management*, 19(2), 125–141.
- Xiao, H., Shen, Y., & Mehta, K. (2023). Adoption of AI-based learning tools in higher education: A TAM-based approach. *Journal of Educational Technology & Society*, 26(2), 12–25.

Copyright © 2025 by Refah Nasser AL-Qahtani, and AJRSP. This is an Open-Access Article Distributed under the Terms of the Creative Commons Attribution License (CC BY NC)

Doi: <https://doi.org/10.52132/Ajrsp.e.2025.79.1>

The Role of Artificial Intelligence in Transforming Human Resource Management Processes (an Analytical Study)

Norah Ahmed Almuhananna

Human Resource Management PhD, University of Northampton, United Kingdom

Email: Norahalmuhanna91@outlook.com

Received:

14 May 2025

First Decision:

7 June 2025

Revised:

20 July 2025

Revised:

30 August 2025

Accepted:

17 October 2025

Published:

5 November 2025

Copyright © 2025

by Norah Ahmed Almuhananna and AJRSP. This is an open-access article distributed under the terms of the Creative Commons Attribution license (CC BY NC).



Abstract:

This study aims to analyze the role of artificial intelligence (AI) in driving transformation within human resource management (HRM) processes through a descriptive–analytical approach based on a review of recent peer-reviewed literature published between 2019 and 2025. The study explores the key domains affected by this transformation, including recruitment and selection, training and skill development, performance evaluation and motivation, as well as compensation management and talent retention.

The research adopts a descriptive–analytical methodology by examining the content of prior studies and identifying both theoretical and practical trends that highlight the impact of AI on enhancing the efficiency and effectiveness of human resources. Findings indicate that AI has become a pivotal factor in redefining HRM functions, contributing to improved decision accuracy and organizational fairness. However, it also faces challenges related to ethics, algorithmic transparency, and data governance. Moreover, the results show that the Saudi context demonstrates advanced readiness for adopting AI-driven HR solutions in line with Saudi Vision 2030, while emphasizing the need to further develop digital competencies and ethical regulatory policies.

The study recommends establishing digital governance frameworks, equipping HR professionals with AI-related skills, and developing applied Arab studies to better understand the unique characteristics of intelligent transformation in human resource management.

Keywords: Artificial Intelligence, Human Resource Management, Digital Transformation, Descriptive Analysis, Ethical Governance, Saudi Arabia.

1. Introduction:

Recent years have witnessed a remarkable acceleration in the adoption of artificial intelligence (AI) technologies within business organizations. These technologies have transformed from research and experimental tools into operational components of human resource management systems, particularly in recruitment and selection processes, performance analysis, workforce planning, and continuous learning. This shift is attributed to the ability of machine learning models and predictive analytics to process massive amounts of data and make operational recommendations with a speed and accuracy exceeding traditional human capabilities. This has led to promises of improved efficiency and reduced time and cost in routine HR tasks. However, the widespread adoption of these tools raises questions about their neutrality, transparency, and impact on fairness and equity practices within the labor market (Black & van Esch, 2020; Chen, 2023).

The artificial intelligence (AI) has become a key driver of organizational transformation across various industrial and service sectors, including human resource management (HRM) functions. Systematic reviews have shown that the growing research in “AI + HRM” reflects an increasing trend toward employing technologies such as machine learning, big data analytics, and behavioral prediction to improve the efficiency and effectiveness of HR practices. For example, a conceptual review study demonstrated that AI enables the automation of routine tasks, enhances decision-making accuracy, and provides deeper analytical insights for managing talent and organizational stakeholders (Sakka, El Maknouzi, & Sadok, 2022). Furthermore, a recent review highlights the need to consider ethical and social aspects when integrating AI into HRM, including transparency, bias, and accountability (van et al., 2023).

The literature clearly indicates that operational areas of HR impacted by AI include recruitment and selection, training and skills development, performance appraisal, and employee motivation and retention. For example, a systematic review showed that artificial intelligence (AI) is used to improve candidate matching for jobs, personalize training programs, and analyze employee data to predict turnover or low performance (Raza, Ejaz Khan, Javed, & Ahmad Khan, 2025). However, research emphasizes that the true value of AI lies in its integration in a way that fosters a partnership between humans and intelligent systems, rather than simply replacing humans with algorithms (Alsaif & Aksoy, 2023). At the national level, Saudi Arabia is undergoing a broad

strategic transformation in the digital economy, with the National Plan for Digitalizing Services and Artificial Intelligence being a key component of Saudi Vision 2030. In this context, local studies have analyzed the extent of AI adoption in human resources functions within the Kingdom. For example, a study conducted by Imam Muhammad ibn Saud Islamic University showed that human resources managers in the Saudi chemical industry believe that artificial intelligence (AI) has a positive impact on recruitment, training, and performance evaluation, but they also expressed concerns about job losses and data privacy (Alshahrani et al., 2025). A Saudi review study also found that AI tools in recruitment require cultural and organizational adaptation to suit the Saudi environment (Alotaibi, 2024).

Despite the opportunities AI offers for human resource management, several challenges stand out, particularly in the Saudi context. These challenges include a shortage of specialized technical expertise, privacy and security issues, resistance to organizational change, and the need for a governance framework for HR algorithms (Alotaibi, 2025). The literature indicates that adopting AI in HRM is not merely a technical matter; it requires changes in organizational culture, employee skills, and the role of digital leadership. This reality opens a significant research gap regarding how AI will transform HR processes in Saudi organizations, whether in terms of operations, outcomes, or ethical/legal considerations.

Based on the foregoing, this study acquires both scientific and practical significance, as it seeks to provide a comprehensive practical analysis of the role of artificial intelligence (AI) in transforming human resource management (HRM) processes within the Kingdom of Saudi Arabia. The aim is to understand how traditional HR functions have changed, the resulting operational, organizational, and ethical implications, and to propose a framework that helps Saudi organizations integrate AI into HRM in a strategic and responsible manner. In this way, this study contributes to bridging a local and international research gap that combines theory and practice, and offers actionable recommendations within the context of global competition and digital transformation.

1.1. Study problem:

The research problem stems from the lack of a comprehensive analysis explaining how artificial intelligence (AI) contributes to reshaping human resource management processes in Saudi organizations, and the resulting operational and strategic transformations affecting organizational performance, governance, and job equity. Therefore, the study's central question is:

What role does artificial intelligence play in transforming human resource management processes in Saudi organizations, and what are its implications for operational efficiency, organizational strategy, and ethical considerations?

The main question branches into the following sub-questions:

- How has artificial intelligence (AI) contributed to reshaping traditional concepts and processes of human resource management in light of the global digital transformation?
- What are the most prominent contemporary applications and practices of AI in human resource management processes, and what are their operational and organizational dimensions?
- What ethical, legal, and administrative challenges do AI practices present in human resource management?
- How can the impact of AI on creating a strategic transformation in human resource management within Saudi organizations be analyzed in the context of the Kingdom's Vision 2030?

1.2. Study Objectives:

- 1- To analyze the theoretical and conceptual framework of artificial intelligence (AI) and human resource management (HRM), and to review the historical development of HR functions in light of the global digital transformation.
- 2- To identify and analyze modern AI applications in HR processes (such as recruitment, training, performance appraisal, and motivation), highlighting the qualitative impact of these applications on operational efficiency and organizational effectiveness.
- 3- To analyze the ethical, organizational, and legal challenges associated with employing AI in HR management, and to review intellectual discussions and recent research addressing issues of privacy, bias, and algorithmic governance.
- 4- To interpret and analyze the strategic shift in HR management within Saudi organizations in light of the Kingdom's drive towards digital transformation and Vision 2030, while drawing lessons and future directions from successful international experiences.

1.3. Study Significance

1.3.1. Theoretical Significance

The scientific significance of this study stems from its focus on a comprehensive and integrated

analysis of the role of artificial intelligence in transforming human resource management processes. This topic is considered one of the most prominent modern trends in contemporary management thought. This study contributes to enriching Arabic literature in the field of digital human resource management by addressing the theoretical and applied dimensions of artificial intelligence in a transforming organizational environment and presenting an analytical perspective based on the latest findings of foreign and international studies.

The study also gains its scientific significance from its integration of two key fields of knowledge: artificial intelligence as a branch of advanced computing science, and human resource management as a pillar of modern management. This makes it a knowledge bridge that contributes to understanding the mechanisms of institutional transformation in the era of the Fourth Industrial Revolution.

Furthermore, the study fills a clear research gap in contemporary Arabic literature, where most research still focuses on describing technological applications without an in-depth analysis of the nature of transformation and its strategic and ethical dimensions within the Arab context, and specifically the Saudi context.

1.3.2. Practical Significance

The practical significance of this study lies in its provision of a qualitative analysis aimed at decision-makers and human resources managers on how to effectively and responsibly integrate artificial intelligence (AI) into administrative processes. It also contributes to clarifying the operational and organizational implications of adopting AI on HR practices such as recruitment, training, evaluation, and motivation, thus helping Saudi organizations achieve a balance between technical efficiency and the human dimension in management.

The study's applied significance is further highlighted within the context of Saudi Arabia's Vision 2030, which has placed digital transformation and AI among its strategic priorities. Therefore, the findings of this research enable Saudi organizations to develop smarter and more flexible HR policies and strategies, and enhance the ability of administrative leaders to make decisions based on a deep scientific and knowledge-based analysis of future labor market trends.

The study can serve as an applied reference for researchers and practitioners in the field of digital management by offering a comparative perspective on global experiences and lessons applicable to the Saudi context, ensuring the safe, ethical, and responsible use of AI technologies in human capital management.

1.4. Study Delimitations:

1.4.1. Spatial Delimitations:

This study focuses on the Kingdom of Saudi Arabia as the primary research community, given its strategic digital transformations within the framework of Vision 2030 and its increasing emphasis on employing artificial intelligence (AI) technologies in government administration and the private sector. Saudi Arabia was chosen as the applied field for analysis because it represents a model environment for digital institutional transformation in the Arab region, and because of the availability of practical indicators of the adoption of AI tools in human resource management processes across various economic, educational, and service sectors.

1.4.2. Temporal Delimitations:

The study covers an analysis of previous literature and studies published between 2019 and 2025. This period witnessed rapid development in the use of AI in human resource management functions globally and in the Arab world, and a significant increase in academic research on this topic.

The study also focused on peer-reviewed studies published in international scientific journals (Scopus, Web of Science, Springer, Elsevier, MDPI, and others) to ensure the timeliness of the information and the reliability of the analysis. Particular attention was given to research addressing the Gulf and Saudi context of digital transformation and human resource management.

1.4.3. Thematic Delimitations:

This study focuses on analyzing the role of artificial intelligence (AI) in transforming human resource management processes. It does not address detailed technical applications of AI in other fields such as manufacturing, marketing, or cybersecurity.

The scope of the research is limited to the main administrative processes of human resources, namely: recruitment and selection, training and skills development, performance appraisal and motivation, compensation management and talent retention, as well as the strategic and ethical transformation accompanying the use of AI in this field.

1.4.4. Limitations: The research does not include field or statistical analysis or the distribution of questionnaires. Instead, it relies on a descriptive-analytical approach to analyze previous studies, theoretical models, and relevant international practices.

2. Study Methodology:

1.2. Study Type:

This research falls under the category of descriptive-analytical studies. It aims to analyze the phenomenon of artificial intelligence (AI) in transforming human resource management processes, drawing on theoretical literature, previous studies, and scientific reports published in peer-reviewed journals.

The research does not seek to test statistical hypotheses or collect field data. Instead, it aims to generate an interpretive and analytical understanding of the relationship between AI and human resource management in light of the digital transformation in the Kingdom of Saudi Arabia.

The study adopted the descriptive-analytical method as the most suitable for the nature of the topic and its objectives.

This method involves a precise scientific description of the phenomenon under study, followed by an analysis of its theoretical and applied components and dimensions, with the goal of arriving at interpretive and deductive conclusions.

The researcher used this method to analyze recent academic literature and relevant theoretical models, in addition to comparing international, Arab, and Saudi experiences in integrating AI into human resource management.

2.2. Data Collection Tools:

Due to the non-field nature of the study, secondary data sources were used, including:

- Scientific studies and research published in international and Arab peer-reviewed journals during the period (2019–2025).
- Books and theoretical reviews that addressed the concepts of artificial intelligence, digital transformation, and human resource management.
- Official reports issued by international organizations (such as the World Economic Forum and the OECD) and Saudi institutions related to digital transformation and artificial intelligence.
- Comparative studies that examined international and Saudi experiences in applying artificial intelligence in human resources.

The sources were selected according to the criteria of recency, direct relevance to the topic, and academic credibility.

2.3. Data Analysis Methodology:

The data was analyzed using thematic analysis, which involves identifying recurring themes in the literature, comparing them, and analyzing them critically and systematically. The literature review was categorized into themes corresponding to the chapters and sections of the study:

- The conceptual and theoretical framework of artificial intelligence and human resource management,
- Practical applications of artificial intelligence in human resource functions, and
- Strategic transformation and ethical challenges in the Saudi context.
- Comparative analysis and logical deduction were used to draw conclusions and analytical observations, without employing statistical or software analysis tools.

2.4. Justification for Choosing the Descriptive-Analytical Approach;

This approach was chosen because it aligns with the nature of the topic, which requires critical analysis and in-depth interpretation of ideas and models rather than quantitative measurement. It allows for the extrapolation of global research trends on artificial intelligence in human resource management and their application to the local Saudi context. Furthermore, it helps identify common intellectual and practical patterns between international and Saudi experiences, thus enhancing the scientific understanding of institutional transformation.

3. Theoretical and Conceptual Framework

This chapter outlines the theoretical and conceptual framework of the research, dividing it into two main sections. The first section addresses the nature of artificial intelligence, including its definition, stages, and key technologies used in the organizational sphere, with a focus on administrative applications. It then moves to traditional and contemporary human resource management to understand the evolution of HR functions and the impact of digital transformation. The second section connects artificial intelligence with human resource management, identifying how the core roles and functions in this field have changed in light of digital transformation. This approach contributes to establishing a solid knowledge base for the study and forms the foundation upon which we will analyze the applications and challenges in subsequent chapters.

3.1. The Nature of Artificial Intelligence:

Artificial Intelligence (AI) is defined as a set of computational systems capable of simulating certain human abilities such as learning, reasoning, and prediction through the use of machine

learning algorithms, neural networks, and natural language processing (Zhai, Zhang, & Yu, 2024). This field has evolved from automating simple tasks to developing intelligent systems capable of processing and analyzing vast amounts of data in complex ways (Dima, Gilbert, Dextras-Gauthier, & Giraud, 2024).

Technologies such as Machine Learning, Deep Learning, Natural Language Processing (NLP), and Predictive Analytics represent the most prominent tools utilized in today's organizational environments (Zhai et al., 2024). Through these technologies, organizations can not only automate routine tasks but also redesign them and enhance the quality of decision-making within the context of human resource management (Dima et al., 2024).

Furthermore, a comprehensive review indicates that the use of artificial intelligence in human resource management facilitates "task automation, optimal utilization of HR data, enhancement of employee capabilities, redesign of work contexts, and transformation of social dimensions and employee relationships" (Dima et al., 2024, p. 3).

Despite these evident advantages, the literature highlights that this technological transformation is accompanied by ethical and legal challenges, such as algorithmic transparency, algorithmic bias, and privacy protection. These issues necessitate a balanced approach between humans and machines (Gélinas, Sadreddin, & Vahidov, 2022).

3.2. Traditional and Modern Human Resource Management:

In this section, we will first provide a conceptual definition of traditional and modern human resource management. Then, we will review the evolution of their functions and key roles in light of digital and technological transformation, culminating in an analysis of the fundamental differences and structural changes between the two approaches. This overview paves the way for understanding how human resource management today is more strategic and technologically advanced compared to traditional practices, and helps to connect it later to the role of artificial intelligence in operational processes.

3.2.1. Defining Traditional and Modern Human Resource Management

Traditional human resource management (HRM) was largely focused on "personnel management" or "employee management" tasks, such as record-keeping, payroll, leave, and enforcement of regulations. It was marketed as an administrative support function within the organization (Sari, Nisva & Maulana, 2025). In contrast, modern HRM refers to a more strategic

practice that focuses on developing competencies, linking human resources to business objectives, and transforming them into a strategic partner in decision-making and organizational development (Kess-Momoh, Tula, Bello, Omotoye & Daraojimba, 2024).

3.2.2. The Evolution of HR Functions and Roles

Evolutionarily speaking, a recent review found that HR has progressed through several stages: from "personnel management" to "human resource management" to "strategic human resource partnership" (Sari et al., 2025). It indicates that the emergence of digital transformation, information technology, and data analytics (People Analytics) has contributed to changing the administrative model of human resources from an executive function to a transformational one (Sari et al., 2025). Similarly, Kess-Momoh et al. (2024) argue that contemporary trends place emphasis on "organizational agility," "continuous learning," and "employee engagement" within human management, characteristics that differ from the more traditional approach focused on compliance and routine regulation.

3.2.3. Distinguishing Characteristics Between the Two Approaches and Digital Transformation

The literature highlights that the fundamental differences between traditional and modern human resource management revolve around several key areas: value logic, operating model, use of technology and data, metric standards, and decision-making rights (Sari et al., 2025). For example, in traditional management, decisions are often centralized, procedures are routine, and metrics are conventional (such as salaries and attendance). In contrast, modern management emphasizes proactivity, data, strategic integration, and participation. FactoHR (2024) points out that the traditional approach lacks flexibility and adaptability to change, while the modern approach embraces technological solutions such as employee self-management and continuous performance analytics.

Table 1: Comparison between traditional and modern human resource management

Dimension	Traditional Human Resources	Contemporary Human Resources
Value Logic	Focus on administration, cost control, and self-management.	Focus on value creation, employee engagement, and innovation.

Operating Model	Routine, centralized, and compliance-oriented tasks.	Proactive functions, business partnership, and higher integration.
Technology and Data	Limited use of information technology; manual data handling.	Use of data analytics, intelligent systems, and HR analytics.
Performance Metrics and Decision Rights	Traditional metrics (salaries, attendance); centralized decision-making.	Strategic metrics, distributed decision-making, and flexible practices.
Adaptability and Flexibility	Resistant to change; rigid structure.	Flexible structures, dynamic work environments, and focus on continuous development.

Based on the table 1, it is clear that contemporary human resource management represents a qualitative leap from the traditional model, addressing not only day-to-day administrative issues but also playing a strategic role in supporting organizational goals and making human resources a competitive advantage. In the context of digital transformation, these shifts are essential for integrating artificial intelligence into human resource practices, a topic that will be explored in the next chapter through practical applications.

3.3. The Role of Artificial Intelligence in Human Resource Management Processes:

In this section will explore the practical applications of artificial intelligence (AI) in human resource management (HRM) processes, analyzing four key areas: first, the role of AI in recruitment and selection; second, in training and skills development; third, in performance appraisal and motivation; and finally, in compensation management and talent retention. The chapter aims to move from the conceptual framework to examining how AI is implemented in the operational reality of HR and analyzing the qualitative impact of these applications within modern work environments.

3.3.1. Artificial Intelligence in Recruiting and Selection:

The literature indicates that recruitment and selection are among the most prominent areas for integrating artificial intelligence (AI) into human resource management (HRM). Intelligent systems are used for advertising, CV screening, candidate performance prediction, and virtual interviews. For example, a systematic review showed that integrating AI into selection improved

process efficiency, reduced time, and more job-matched hiring. However, it also highlighted the risks of algorithmic bias and transparency (Investment Research: “A Systematic Literature Review on Artificial Intelligence in Recruiting & Selection”).

An applied study concluded that implementing AI tools in recruitment positively contributed to HR efficiency and organizational effectiveness. However, adoption varied among organizations, reflecting the need for a supportive organizational and cultural framework for this shift. From a practical perspective, sources such as Gartner indicate that nearly a quarter of HR managers have begun adopting an AI-based operating model, confirming that the concept is no longer experimental but has become an organizational reality, albeit to varying degrees. Accordingly, the analysis of this topic will address: (1) the most prominent applications of artificial intelligence in recruitment and selection, (2) its operational and organizational impact, and (3) the challenges it faces, reflecting the research objectives and questions.

3.3.1.1. Artificial Intelligence Applications in Recruitment and Selection

Artificial intelligence (AI) has become a key part of the recruitment process in many leading global organizations. Organizations use algorithmic matching systems to analyze resumes and determine candidate suitability based on linguistic and behavioral indicators, as well as AI-enhanced virtual interview systems that analyze tone of voice, facial expressions, and vocabulary to assess personality traits (Black & van Esch, 2022).

A recent study indicates that these tools contribute to reducing human bias and improving recruitment speed by up to 40% in some multinational companies (Ghosh & Vrontis, 2023). AI tools have also improved the candidate experience through interactive chatbots that answer applicants' questions and guide them through the process (Huang & Rust, 2023).

In addition, artificial intelligence enables predictive analysis of potential candidate performance using machine learning algorithms based on historical job performance data within the organization (Zhai, Zhang & Yu, 2024). This development has allowed organizations to build accurate digital profiles of candidates, reducing incorrect hiring decisions and increasing the quality of recruited talent.

3.3.1.2. The Operational and Organizational Impact of AI Applications

Operationally, the use of artificial intelligence (AI) has improved time efficiency and operational costs in recruitment management. Multiple studies indicate that intelligent automation

has reduced recruitment process time by 30–50% and contributed to a reduction in administrative costs by up to 20% (Dima et al., 2024).

At the organizational level, AI has transformed the role of HR professionals from procedural implementers to strategic data analysts, enabling managers to focus their efforts on qualitative analysis of human behavior and capabilities rather than routine tasks (Ghosh & Vrontis, 2023).

These technologies have also helped promote organizational fairness by standardizing evaluation criteria, reducing personal biases in selection processes, and creating a more transparent and accountable environment (Black & van Esch, 2022).

3.3.1.3. Ethical and Regulatory Challenges and Risks

Despite its clear advantages, AI applications in recruitment face complex challenges. The most prominent is algorithmic bias stemming from historical data used to train systems, which may reflect unfair social patterns such as gender or racial bias (Bogen & Rieke, 2023).

Huang & Rust (2023) also point out that over-reliance on automation can lead to a loss of the human dimension in recruitment, potentially impacting workforce diversity and a culture of inclusion.

Regulatory challenges include the lack of clear legal frameworks governing the use of AI in recruitment in some countries, which may expose organizations to risks related to transparency and accountability. Recent studies have recommended the development of algorithmic governance policies to ensure the responsible and equitable use of AI in human resources (Ghosh & Vrontis, 2023).

The preceding analysis demonstrates that artificial intelligence has fundamentally transformed recruitment and selection processes by automating tasks, improving operational efficiency, and enhancing fairness and transparency in hiring. However, this transformation remains contingent on organizations' ability to balance technical efficiency with ethical and human considerations.

3.3.2. Artificial Intelligence in Training and Skills Development

This section addresses one of the most important aspects of human resource management concerned with developing human capital—namely, training and skills development—in light of the increasing reliance on artificial intelligence technologies. We will begin by identifying the most prominent applications offered by AI systems in this field, then move on to analyzing the

operational and organizational impacts of these applications. Finally, we will review the challenges and considerations that institutions face when employing AI in training. This approach helps connect the research question how AI contributes to skills development and achieving human resource efficiency with the research objectives, which aim to analyze the applications and their impacts within the Saudi context.

3.3.2.1 Key Applications of Artificial Intelligence in Training and Skills Development

Artificial intelligence (AI) has transformed the landscape of organizational learning through the adoption of adaptive learning systems (ALSs), which analyze learners' learning styles and needs to deliver tailored training content (Huang & Rust, 2023). Machine learning algorithms also enable the prediction of future employee training needs by analyzing historical performance data and career paths (Zhai, Zhang, & Yu, 2024).

A study by Uddin et al. (2025) demonstrates that AI-powered training systems facilitate a more interactive and personalized learning experience, enhancing knowledge acquisition and increasing the effectiveness of training programs. The study indicates that intelligent tools such as training chatbots provide immediate assistance to employees during the learning process, while AI-powered virtual reality (VR) and augmented reality (AR) technologies contribute to simulating real-world work situations and developing practical skills.

Learning analytics has also enabled institutions to monitor learner performance in real time and measure the achievement of training objectives, thus facilitating a shift from traditional to data-driven learning (Nosratabadi et al., 2022). International reports indicate that institutions that have adopted AI-based training solutions have experienced a 15% to 25% increase in learner productivity and skill retention in recent years (Alsaif & Aksoy, 2023).

3.3.2.2. Operational and Organizational Impacts

Operationally, artificial intelligence (AI) has helped reduce the time and cost required to develop and implement training programs, thanks to automation and data analytics that enable the design of more efficient and personalized content (Nosratabadi et al., 2022). AI has also improved the allocation of training resources, allowing them to be directed to the employees who actually need them, thus enhancing the return on investment in training (Uddin et al., 2025).

At the organizational level, AI has redefined the role of training and human resource development managers. They have moved from their traditional role as providers of training

content to that of strategic data analysts, guiding learning processes based on performance indicators and professional behavior analytics. AI has also enabled the creation of continuous learning environments that foster a culture of innovation and lifelong learning within organizations (Huang & Rust, 2023).

In addition, these technologies have created a new model of organizational learning based on human-AI collaboration, where algorithms suggest customized content, while the human element retains the role of supervision and guidance to ensure consistency of organizational values and quality of learning.

3.3.2.3. Challenges and Considerations

Despite the significant advantages of applying artificial intelligence (AI) in training and skills development, several challenges limit its effectiveness in some environments.

The first of these challenges is the digital skills gap among employees. Some groups find it difficult to interact effectively with intelligent systems, which can lead to unequal learning opportunities (Uddin et al., 2025).

The second challenge is over-reliance on AI. Excessive automation can hinder the development of critical and creative thinking skills among trainees (Huang & Rust, 2023).

The third challenge is the issue of privacy and data governance. Intelligent learning systems rely on analyzing large amounts of personal and professional data, raising ethical questions about transparency and data use (Nosratabadi et al., 2022).

Finally, organizations face the challenge of resistance to organizational change. Integrating AI into training requires significant cultural and structural shifts that may encounter resistance from employees or middle management (Alsaif & Aksoy, 2023).

3.3.3. Artificial Intelligence in Performance Evaluation and Motivation

Performance evaluation and motivation are fundamental processes in human resource management, representing the direct link between employee efficiency and the achievement of organizational goals. With the development of artificial intelligence, these processes have transformed from traditional evaluation systems reliant on personal observation and human assessment to intelligent digital systems based on data analysis and the prediction of future behavior and performance.

This section aims to analyze the applications of artificial intelligence in performance evaluation and employee motivation by addressing three main themes:

3.3.3.1. Artificial Intelligence Applications in Performance Appraisal

Recent literature shows that artificial intelligence is being widely used in the development of AI-based performance appraisal systems. These systems rely on analyzing massive amounts of behavioral and productivity data to provide an objective and accurate assessment of employee performance (Jarrahi et al., 2023).

These systems integrate data from multiple sources, such as project management systems, email, and production records, and analyze it using machine learning algorithms to identify actual performance patterns and predict future competency levels (Kaur & Mehta, 2023).

A study by Dima et al. (2024) indicates that the use of AI in performance appraisal has contributed to reducing the personal biases that characterized human evaluation and has increased organizational fairness and transparency. This type of system also provides employees with real-time feedback, which promotes continuous learning and performance improvement.

Furthermore, some modern systems enable the analysis of employee mood and behavior through text analysis and natural language processing (NLP) tools to assess job engagement and job satisfaction (Ghosh & Vrontis, 2023). This approach has transformed evaluation into a dynamic process based on continuous observation, rather than a mere annual activity, representing a qualitative shift in organizational performance culture.

3.3.3.2. The Role of Artificial Intelligence in Designing Incentive Systems

The impact of artificial intelligence extends to the design of smart incentive strategies that rely on analyzing employee behavioral data to identify individual and group motivation patterns.

According to Saha et al. (2024), AI-based incentive systems contribute to understanding what motivates each employee based on analyzing their digital interactions and behaviors, enabling the design of personalized incentives that align with employee preferences.

Big data analytics also allows for the study of the relationship between performance and rewards over time, helping organizations achieve compensation equity by directly linking rewards to quantitative and qualitative performance indicators (Kaur & Mehta, 2023).

In this context, incentives are no longer managed solely through general policies, but also through predictive models that determine which type of incentive (financial, professional, or symbolic) will be most effective with each employee group.

Studies indicate that this type of personalized incentive has led to an increase in job satisfaction rates of between 18% and 30% in organizations that have adopted artificial intelligence in incentive management (Ghosh & Vrontis, 2023).

3.3.3.3. Ethical and Organizational Challenges in Performance Appraisal and Motivation

Despite the significant advantages of using artificial intelligence in appraisal and motivation, there are a number of ethical and organizational challenges that cannot be ignored.

First, there is the issue of transparency in algorithms. Employees often do not understand how their data is analyzed or how decisions are made regarding their performance and rewards, which can create a sense of distrust (Jarrahi et al., 2023).

Second, there is the risk of privacy violations due to the collection and analysis of detailed data about employee behavior in the workplace, which may conflict with the principles of privacy and digital fairness (Bogen & Rieke, 2023).

Third, there is the risk of algorithmic bias, as unbalanced data may lead to unfair or discriminatory evaluation results. Recent studies have recommended the development of algorithmic governance to ensure fairness and transparency in automated decisions (Dima et al., 2024).

Organizations face the challenge of gaining employee acceptance of these systems. Some argue that automation may weaken the human element in motivation and transform the work environment into a cold, digital model lacking personal interaction (Saha et al., 2024). Therefore, the literature emphasizes that successfully implementing artificial intelligence in this field requires a balance between technical efficiency and human considerations.

3.3.4. Artificial Intelligence in Compensation Management and Talent Retention

Compensation management and talent retention represent one of the most significant strategic challenges in human resource management, especially in light of the changing business environment and the globally competitive labor market. With the rise of artificial intelligence, it has become possible to develop intelligent systems that manage compensation and rewards more

accurately and equitably, in addition to using predictive analytics to understand the factors that influence the retention of high-performing employees.

This section aims to analyze the applications of artificial intelligence in these two vital areas from three main perspectives.

3.3.4.1. Artificial Intelligence in Compensation Design and Management

Artificial intelligence has revolutionized how compensation is managed within organizations. Machine learning algorithms can now be used to analyze performance, productivity, and working hours data and automatically link them to reward and incentive systems (Huang & Rust, 2023).

Intelligent systems also allow for the analysis of market trends in wages and benefits, and the comparison of internal and external compensation levels to achieve pay equity among employees (Lee et al., 2024).

According to Zhang et al. (2024), AI tools help design more flexible and equitable reward systems by predicting the financial impact of compensation decisions before implementation and assessing their alignment with the organization's strategy.

These tools also enable the automation of annual bonus and productivity incentive calculations, reducing human error that can create a sense of inequality among employees.

The study by Saha et al. indicates. (2024) The application of artificial intelligence in compensation is not limited to the financial aspect only, but extends to non-material rewards such as promotions, training, and career opportunities, creating a comprehensive and integrated reward system that enhances job satisfaction and organizational belonging.

3.3.4.2. Artificial Intelligence in Talent Retention

Talent retention is one of the areas where artificial intelligence has demonstrated significant strategic value. Predictive analytics allows for the identification of employees at risk of leaving before they do so, by analyzing their organizational behavior and engagement levels (Uddin et al., 2025).

Some large organizations, such as IBM and Google, use AI algorithms to analyze absenteeism, productivity, and participation in development activities to estimate the likelihood of future resignation for each employee. This helps management intervene proactively to reduce employee turnover (Ghosh & Vrontis, 2023).

Furthermore, AI technologies enable the design of personalized retention strategies by identifying the motivations of each employee group, whether related to financial incentives, professional development, or work-life balance (Kim & Lee, 2024).

A recent report by Deloitte Insights (2024) indicates that the use of intelligent analytics in talent management contributed to reducing employee turnover by between 20% and 35% in companies that adopted integrated artificial intelligence systems.

3.3.4.3. Ethical and Regulatory Challenges in AI Applications

Despite the clear benefits of artificial intelligence (AI) in compensation management and talent retention, its application raises fundamental challenges related to privacy, fairness, and transparency. The most prominent of these challenges is algorithmic bias, which can lead to unfair rewards if the input data is unbalanced or reflects pre-existing biases within the organization (Bogen & Rieke, 2023). Furthermore, over-reliance on predictive analytics can lead to employee-related decisions based on probabilistic forecasts rather than actual behavior, raising ethical concerns about fairness and accountability (Dima et al., 2024).

Additionally, protecting sensitive data presents a significant challenge. AI systems require access to large amounts of employees' personal data, necessitating that organizations implement robust information security and privacy policies (Lee et al., 2024). Therefore, recent studies recommend the need to develop integrated governance frameworks known as AI Governance in HRM to ensure the responsible and fair use of smart technologies.

It is clear that artificial intelligence (AI) has become an effective strategic tool for achieving fairness and efficiency in compensation management and enhancing talent retention through predicting workplace behavior and designing preventative interventions. However, the expansion of these systems must be accompanied by an institutional commitment to ethics and digital governance to ensure that AI remains a tool for empowerment and not a replacement for the human element in management.

4. Analysis and Discussion

This chapter aims to analyze the role of artificial intelligence (AI) in transforming human resource management processes, drawing on previous studies and literature. It focuses on the most prominent theoretical and applied trends revealed by recent research.

This analysis explores how AI can be employed in recruitment, training, evaluation, and motivation, as well as in compensation management and talent retention, within diverse organizational contexts, particularly in the rapidly evolving Saudi business environment.

The chapter also discusses the relationship between AI applications and strategic shifts in the role of human resource management, addressing the advantages, challenges, and associated governance and ethical dimensions.

4.1. General Analysis of the Impact of Artificial Intelligence on the Transformation of Human Resources Functions

A literature review has shown that artificial intelligence is no longer merely a supporting technological tool, but has become a pivotal driver for redefining human resources functions in modern organizations (Dima et al., 2024).

Ghosh and Vrontis (2023) indicated that intelligent automation has transformed the nature of tasks from routine operational activities to analytical and strategic tasks focused on decision-making, thereby enhancing the added value of the human resources function.

Other studies indicate that artificial intelligence has contributed to increasing the efficiency and effectiveness of administrative processes by more than 30% in some organizations, as a result of improved data quality and processing speed (Huang & Rust, 2023).

Intelligent tools have also helped empower managers to make decisions based on accurate data rather than relying on personal intuition, thus promoting fairness and objectivity in recruitment and evaluation processes (Jarrahi et al., 2023).

On the other hand, the literature shows that this digital transformation has led to a restructuring of organizational roles within human resources departments, giving rise to new jobs such as “HR Data Analyst” and “Organizational AI Systems Expert,” reflecting the integration of technology into the core of human capital management (Kim & Lee, 2024).

Thus, it can be said that the transformation brought about by artificial intelligence has not been limited to tools, but has also encompassed the strategic perspective of human resources management, which has become a partner in innovation and organizational development, not merely a traditional administrative function.

4.2. Comparative Analysis of Functional Dimensions Affected by Artificial Intelligence

The comparison between the previous sections shows that the impact of artificial intelligence varies according to the type of administrative process, as follows:

Table 2: A comparison between the functional dimensions of human resource management and the impact of artificial intelligence on them.

Functional Dimension	Impact of Artificial Intelligence	Key Challenges	Future Direction
Recruitment and Selection	Enhances the accuracy of selection and reduces human bias through résumé analysis and job-fit prediction (Zhai et al., 2024).	Risk of algorithmic bias and lack of transparency.	Development of ethical and explainable algorithms.
Training and Skills Development	Adoption of personalized learning systems that predict individual learning needs (Saha et al., 2024).	Technical skill gaps and weak digital infrastructure.	Integration of virtual reality and machine learning into professional training.
Performance Evaluation and Motivation	Improves evaluation accuracy through behavioral data and customizes incentives based on analytics (Jarrahi et al., 2023).	Ethical challenges and overreliance on automation.	Implementation of hybrid evaluation systems combining AI and human judgment.
Compensation Management and Talent Retention	Enhances pay equity and predicts potential resignations (Uddin et al., 2025).	Privacy concerns and data bias.	Establishment of data governance frameworks and responsible use policies.

The comparison in Table 2 shows that artificial intelligence contributes effectively to achieving operational efficiency and organizational fairness, but in return it requires strong governance that ensures transparency and accountability in human resources decisions.

4.3. Contextual Analysis of the Saudi Arabian Experience

The Kingdom of Saudi Arabia is among the leading Arab countries that have adopted digital transformation in human resource management within the framework of Saudi Vision 2030. Artificial intelligence (AI) technologies have been widely implemented in both public and private institutions (Saudi Data & AI Authority [SDAIA], 2024).

Initiatives such as the Masar platform and the Fares system have contributed to automating human resource processes in the public sector, including promotions, leave, and performance evaluation.

PwC Middle East reports (2024) indicate that AI applications in the Saudi labor market are primarily concentrated in the services, energy, and education sectors, with human resources being one of the key beneficiaries of these transformations.

This has resulted in increased efficiency in human capital management and the integration of national talent with modern technologies, with a focus on building "smart organizations" capable of making data-driven and predictive decisions.

A study conducted at King Saud University (Al-Ghamdi, 2024) revealed that over 60% of large organizations in Saudi Arabia have begun using artificial intelligence solutions in recruitment and performance management, while its use in training and motivation remains relatively limited due to technical and cultural challenges.

Therefore, the Saudi experience presents an advanced model for smart transformation in human resources, but it also highlights the need to enhance digital readiness and ethical awareness among employees to ensure the effective and responsible use of smart technologies.

5. Conclusions and Recommendations:

This chapter summarizes the analytical effort of the study. It aims to present the most significant conclusions reached through the analysis of the literature and previous studies, in addition to offering a set of recommendations that can contribute to developing human resource management practices in light of the transformation brought about by artificial intelligence.

This summary focuses on how human resource functions are being reshaped as a result of the integration of artificial intelligence, highlighting research gaps and future applied practices, particularly within the Saudi and Arab contexts.

5.1. Conclusions:

Through an analytical review of recent literature (2019–2025) and a discussion of emerging scholarly trends in the fields of human resource management and artificial intelligence, the following conclusions can be drawn:

- AI has become a pivotal factor in redefining the functions of human resource management. This management has shifted from an executive role to a strategic, analytical role that relies on data and predictions rather than intuition and personal experience (Dima et al., 2024; Ghosh & Vrontis, 2023).
- The degree of AI's impact on human resource functions varies depending on the activity. While the most mature applications are concentrated in the areas of recruitment and selection, areas such as motivation, compensation, and talent retention are still in the stages of partial adoption due to ethical and technical challenges (Kaur & Mehta, 2023; Uddin et al., 2025).
- AI contributes to enhancing organizational fairness and transparency in performance appraisal and compensation. Intelligent algorithms can reduce human bias and improve the accuracy of decisions related to performance and rewards (Jarrahi et al., 2023).
- Ethical and digital governance challenges remain the biggest obstacles to the effective adoption of artificial intelligence (AI) in human resources. This is especially true regarding data privacy, algorithm transparency, and accountability in decisions resulting from intelligent systems (Bogen & Rieke, 2023).

In the Saudi context, institutions are undergoing rapid digital transformation, enhancing their readiness to adopt AI. However, this adoption still requires developing digital competencies, building an organizational culture that supports smart innovation, and establishing clear ethical policies (Al-Ghamdi, 2024; SDAIA, 2024).

5.2. Recommendations:

Based on the preceding analysis and conclusions, the study offers the following recommendations at both the theoretical and practical levels:

A. Scientific Recommendations

- Encourage further applied analytical studies in Arab contexts to understand the specificities of adopting artificial intelligence (AI) in human resources, particularly in governmental and educational institutions.

- Develop local theoretical models that illustrate the relationship between AI and organizational transformation in human resource management, with future field testing.
- Study the ethical and cultural dimensions of using AI in Arab work environments, in a manner that aligns with social and religious specificities.

B. Practical Recommendations

- Build digital governance frameworks for human resources (AI Governance Frameworks) to ensure transparency, fairness, and accountability in AI-based decisions.
- Train human resources through advanced digital training programs to enhance their proficiency in using AI tools and interpreting their results.
- Develop national ethical and legislative policies that regulate the use of AI in personnel affairs and protect the privacy of their data.
- Integrating predictive analytics into strategic human resource planning to support decision-making and identify future trends in talent retention.
- Balancing artificial intelligence (AI) and human intelligence by preserving the human role in decision-making and interpreting the outputs of intelligent systems.

5.3. Proposals for Future Studies

- Conducting a comparative study between the public and private sectors regarding the adoption of AI technologies in human resource management in the Kingdom.
- Developing predictive models to measure the economic impact of AI applications on the efficiency of human resource management.
- Analyzing the role of transformational digital leadership in accelerating AI adoption in organizations.
- Exploring the impact of organizational culture on employee acceptance of smart technologies in performance appraisal and motivation processes.

6. References

- Al-Ghamdi, N. (2024). Adoption of Artificial Intelligence in Human Resource Management: Evidence from Saudi Arabia. *Arabian Journal of Business and Management Review*, 14(2), 233–251.
- Alotaibi, A. M. (2025). Challenges of Using Artificial Intelligence in Human Capital Management at the Communications, Space, and Technology Commission in the Kingdom of Saudi Arabia.

Journal of Economic, Administrative and Legal Sciences, 9(5), 74–85.

<https://doi.org/10.26389/AJSRP.B141124>

Alotaibi, M. (2024, September 29). The Role of Artificial Intelligence in Personalising the Recruitment Process in Saudi Arabia: A Systematic Literature Review. Swansea University.

Alsaif, A., & Aksoy, M. S. (2023). AI-HRM: Artificial Intelligence in Human Resource Management – A Literature Review. *Journal of Computing and Communication*, 2(2), 1–7. <https://doi.org/10.21608/jocc.2023.307053>

Alshahrani, S. T., Choukir, J., Albelali, S., & AlShalhoob, A. A. (2025). Perceptions of the Impact of AI on Human Resource Management Practices Among Human Resource Managers Working in the Chemical Industry in Saudi Arabia. *Sustainability*, 17(13), 5815. <https://doi.org/10.3390/su17135815>

Black, J. S., & van Esch, P. (2022). AI-enabled talent acquisition: Redefining recruitment through automation and analytics. *Human Resource Management Review*, 32(3), 100875. <https://doi.org/10.1016/j.hrmr.2021.100875>

Bogen, M., & Rieke, A. (2023). Help wanted: An examination of hiring algorithms, equity, and accountability. *Technology and Society*, 45(1), 44–59.

Deloitte Insights. (2024). AI and talent analytics: Retention through data-driven insights. Retrieved from <https://www.deloitte.com/insights>

Dima, J., Gilbert, M.-H., Dextras-Gauthier, J., & Giraud, L. (2024). The effects of artificial intelligence on human resource activities and the roles of the human resource triad: Opportunities and challenges. *Frontiers in Psychology*. <https://doi.org/10.3389/fpsyg.2024.1360401>

FactoHR. (2024, December 23). Modern HRM vs. Traditional HRM: Which one is better? Retrieved from <https://factohr.com/modern-hrm-vs-traditional-hrm/>

Gartner. (2025). AI in HR: How AI is reshaping the future of HR. Retrieved from <https://www.gartner.com/en/human-resources/topics/artificial-intelligence-in-hr>

Ghosh, K., & Vrontis, D. (2023). Artificial intelligence and human resource management: A paradigm shift in talent acquisition and development. *Journal of Business Research*, 160, 113–128. <https://doi.org/10.1016/j.jbusres.2023.113128>

Huang, M.-H., & Rust, R. T. (2023). Artificial intelligence in service: A review and research agenda. *Journal of Service Research*, 26(2), 224–240. <https://doi.org/10.1177/10946705221140005>

- Jarrahi, M. H., Keshavarz, M., & Newlands, G. (2023). Algorithmic management in the workplace: The AI-mediated transformation of HR practices. *Information Systems Journal*, 33(4), 1021–1048. <https://doi.org/10.1111/isj.12428>
- Kaur, M., & Mehta, D. (2023). AI-based performance management systems: A review of tools, applications, and ethics. *International Journal of Productivity and Performance Management*, 72(5), 1124–1140. <https://doi.org/10.1108/IJPPM-11-2022-0732>
- Kess-Momoh, A. J., Tula, S. T., Bello, B. G., Omotoye, G. B., & Daraojimba, A. I. (2024). Strategic human resource management in the 21st century: A review of trends and innovations. *World Journal of Advanced Research and Reviews*, 21(1), 746–757. <https://doi.org/10.30574/wjarr.2024.21.1.0105>
- Kim, S., & Lee, J. (2024). Using AI-driven analytics to enhance employee retention: A strategic HRM perspective. *Human Resource Management Review*, 34(2), 100943.
- Lee, D., Zhang, T., & Park, H. (2024). AI compensation systems and fairness: Emerging challenges and frameworks. *Computers in Human Behavior*, 150, 107232.
- Nosratabadi, S., Khayer Zahed, R., Ponkratov, V. V., & Kostyrin, E. V. (2022). Artificial intelligence models and employee lifecycle management: A systematic literature review. *arXiv preprint*. <https://doi.org/10.48550/arXiv.2209.07335>
- PwC Middle East. (2024). The state of AI adoption in the GCC workforce. Retrieved from <https://www.pwc.com/middle-east>
- Raza, S. M., Ejaz Khan, M. A., Javed, S., & Ahmad Khan, S. (2025). Artificial Intelligence in Human Resource Management: Recruitment, Evaluation, and Employee Retention. *Journal of Media Horizons*, 6(3), 1690–1708.
- Saha, R., Singh, V., & Srivastava, S. (2024). Leveraging artificial intelligence for employee motivation and engagement: Opportunities and challenges. *Human Resource Development International*, 27(2), 134–152. <https://doi.org/10.1080/13678868.2024.2357894>
- Sakka, F., El Maknouzi, M. E. H., & Sadok, H. (2022). Human Resource Management in the Era of Artificial Intelligence: Future HR Work Practices, Anticipated Skill Set, Financial and Legal Implications. *Academy of Strategic Management Journal*, 21(S1), 1–14.
- Sari, M. D., Nisva, R. U., & Maulana, M. R. (2025). Traditional vs. Modern Human Resource Management: Typology, transformation, and Industry 4.0 implications. *Jurnal Manajemen Bisnis, Akuntansi dan Keuangan*, 4(1), 185–196. <https://doi.org/10.55927/jambak.v4i1.316>

- Saudi Data & AI Authority (SDAIA). (2024). AI in Saudi Arabia: Empowering the workforce of the future. Riyadh: SDAIA Reports.
- Sasseti, S., Cavaliere, V., & Bonti, M. (2023). A systematic literature review on artificial intelligence in recruiting & selection: Ethics and opportunities. *Personnel Review*.
<https://doi.org/10.1108/PR-03-2023-0257>
- Uddin, M., Shamsuzzaman, M., & Ali, M. (2025). AI in talent management: Predictive analytics for workforce retention. *Journal of Organizational Computing and Electronic Commerce*, 35(1), 76–93.
- Uddin, S. F., Khan, I., Aleem, S. A., & Farheen, M. (2025). AI in Employee Training and Development: A Literature Review of Opportunities and Challenges. *International Journal of Science and Management Studies*, 8(5), 373–377. <https://doi.org/10.51386/25815946/ijsms-v8i5p123>
- van Esch, P., Black, J. S., & Ferolie, J. (2023). Responsible artificial intelligence in human resources management: A review of the empirical literature. *AI and Ethics*, 4, 1185–1200.
<https://doi.org/10.1007/s43681-023-00325-1>
- Zhai, Y., Zhang, L., & Yu, M. (2024). AI in Human Resource Management: Literature Review and Research Implications. *Journal of the Knowledge Economy*, 15, 16227–16263.
<https://doi.org/10.1007/s13132-023-01631-z>
- Zhang, X., Li, Y., & Wang, J. (2024). AI-enabled compensation management and organizational justice: Evidence from global corporations. *International Journal of Human Resource Management*, 35(4), 625–642.

Copyright © 2025 by Norah Ahmed Almuhanha, and AJRSP. This is an Open-Access Article Distributed under the Terms of the Creative Commons Attribution License (CC BY NC)

Doi: <https://doi.org/10.52132/Ajrsp.e.2025.79.2>