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The acceptance of artificial intelligence in Performance Evaluation and Training Development: Analysis of Influencing from the Perspective of Employees

Juan Hong

Master of Arts in Human Resource Management

National College of Ireland

August 2025

Abstract

With the widespread application of artificial intelligence (AI) in human resources (HR), its use in key areas such as performance management (PM) and training and development (TD) has been increasing. However, research on the differences in employees' acceptance in different application scenarios and its influencing factors is still relatively limited. This study, from the perspective of employees, comparatively analyses the differences in acceptance between the PM and TD scenarios and explores the key factors influencing their acceptance. The research adopted a quantitative research methodology, a total of 89 valid samples were collected from employed participants through a questionnaire survey, and statistical analysis methods were employed to analyses the data and present the results. The research results show that employees' acceptance of both scenarios is at a relatively high level, with the acceptance of TD slightly higher than that of PM. The key factors influencing acceptance also vary in different scenarios. In PM scenario, perceived efficiency is the strongest influencing factor, and the lack of interpersonal communication has a positive impact on acceptance. In TD, company support and transparent recommendations are key influencing factors. The findings of this study enrich the research application of AI technology acceptance models in the HR field and provide practical references for enterprises to introduce AI in different HR scenarios.

Keywords: Artificial Intelligence, Human Research Management, Performance Management, Training Development, Employee acceptance

Thesis Declaration Page

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Acknowledgements

I can complete this thesis successfully thanks to the support of many people.

First and foremost, I would like to sincerely thank my supervisor Elaine Rossiter, for her meticulous guidance and patient support throughout the course of this dissertation. She provided professional academic guidance and valuable advice, which enabled me to complete my research successfully.

Secondly, I would like to thank my friends for their encouragement and support during the period of my writing my thesis, which helped me to overcome the most challenging period and maintain a positive attitude.

Finally, I would like to thank all the participants in the questionnaire survey, without their active cooperation and support, the data and analysis of this study could not be completed successfully.

Table of Contents

Chapter one—— Introduction

1.1 Introduction

This thesis aims to explore employees' acceptance of the application of artificial intelligence (AI) in two key areas of human resources: performance management (PM) and training development (TD). Through comparative analysis, it delves further into the key factors influencing acceptance. This chapter will outline the purpose and research questions of this study, review the literature gaps, elaborate on the theoretical basis, summarize the research methods adopted, and explain the overall structure of the thesis.

Artificial intelligence (AI) embodies the new round of technological innovation and key factor promoting the evolution of human resource management (HRM) functions (Bondarouk and Brewster, 2016) and has been gradually introduced into practice. It has attracted widespread attention especially in recruitment screening, performance management and employee training and development (Qamar *et al.,* 2021). AI is becoming an important force driving organizational change, significantly enhancing efficiency and innovation capabilities as well as changes in market or global competitiveness (Haenlein and Kaplan, 2019). The success of an organization largely depends on how successfully it combines individual, process and technical functions to provide transformational value at the best cost (Balamourougane *et al.,*2019). In the field of human resources, this trend is driving a major transformation in its functions and positioning. Studies have shown that the application of artificial intelligence in human resource management includes recruitment and screening (Oswald et al., 2020), performance evaluation (Chukwuka and Dibie, 2024), and employee allocation (Karatop *et al.,* 2015). In multiple fields such as training (Maity,2019) and development (Bhatt and Muduli, 2023). AI tools have brought about automation, data-driven and predictive capabilities (Jarrahi,2018). Although AI has enhanced the efficiency and data insight of HR, its application in scenarios highly related to employees' vital interests, such as performance management evaluation and training development, still faces many challenges. Employees' concerns regarding their privacy, fairness, and lack of interpersonal interaction have become increasingly prominent (Leicht-Deobald *et al.,* 2022).

In this context, it is important to explore how employees view the application of AI in key HR fields and their attitudes towards the acceptance of AI in different scenarios.

1.2 Research Objectives and Research Questions

Research objective

With the wide application of AI in organizational management practices, enterprises recognise its potential in HRM, especially in key areas such as PM and TD. However, employees' acceptance of AI and whether they perceive it as a trustworthy management tool, directly affects the effectiveness and sustainability of its applications.

This study aims to deeply explore the acceptance of AI in the two major fields of HRM from the perspective of employees, compare whether there are significant differences between the two scenarios, and further identify the influencing factors that play a key role in different situations. The focus is on examining the relative action mechanisms of variables such as performance expectations, social impact, perceptions of fairness, privacy concerns, and interpersonal interaction, it will reveal scenario differences and psychological mechanisms, provide theoretical supplements for the expansion of AI technology acceptance models in the HR field, and offer empirical evidence for organizations to effectively promote AI integration.

Research question

1. Do employees remain open to the potential use of artificial intelligence in HR applications?

2. In the application scenarios of artificial intelligence for performance management evaluation and training development, which one do employees tend to accept more?

3. In the two application scenarios of performance management evaluation and training development, among the three factors of privacy concerns, perceptions of fairness, and lack of interpersonal interaction, which one is most significant?

In response to the above research questions, there is currently a lack of systematic studies in the literature that compare the acceptance of AI in performance management and training development from the perspective of employees and its influencing factors. Based on this, the following will further describe the literature gaps targeted by this research.

3. Research Gap

Although the research on artificial intelligence in human resource management has shown an increasing trend in recent years (Abu et al., 2024), existing studies have explored the application models, potential value and challenges faced by AI in human resource practice. However, there are still certain limitations (Budhwar *et al.,* 2022; Arslan *et al.,*2022; Gong *et al.*,2025; Benabou and Touhami,2025).

Most of the literature focuses on the discussion at the technical level (Jatobá *et al.,* 2019), and relatively few conduct in-depth analyses from the perspective of employees on their psychological responses and willingness to accept AI-driven HR practices (Lase and Nkosi, 2023). However, the successful implementation of AI technology depends on the adoption and adaptation of the directly affected employees (Davis,1989; Venkatesh *et al.,*2003). If employees fail to understand or identify with the AI decision-making mechanism, they may develop resistant or even evasive behaviours, which weakens its actual effectiveness and further affects their job satisfaction, trust and organizational commitment (Kolatshi, 2017; Sweiss and Yamin,2024; Park *et al.,* 2024; Taslim *et al.,*2025).

In terms of research scope, existing studies have examined the application of AI in isolated HR functional modules but lack systematic comparative analyses of acceptance in interrelated and comparative functional areas such as performance management and training development. With the enhancement of employees' awareness of AI, understanding the differences in employees' acceptance of AI in different application scenarios is of great significance for organizations in promoting the implementation of AI tools and improving the effectiveness of human resource management (Park et al., 2021; Dell'Acqua *et al.,*2023). Performance management and training development are directly related to the performance and career growth of on-the-job employees. Their acceptance not only depends on the maturity of the technology itself but is also profoundly influenced by social and psychological factors (Davis, 1989; Venkatesh *et al.*, 2003; Tambe *et al.,*2019). These factors have a profound impact on both employee adoption behaviour and organizational performance (Venkatesh *et al.,* 2003; Tambe *et al.,* 2019).

To address the identified research gaps, the following will outline the theoretical foundations of this study.

4. Rationale for this study

This study's theoretical framework integrates both the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). In the initial design of this study, the perceived usefulness and perceived ease of use of TAM were intended to analyse the overall acceptance of AI by employees in HRM and the differences between the two application scenarios (PM and TD). However, due to the limitations of the sampling method, it is impossible to confirm that all the organizations where the respondents are located have deployed AI technology in HRM, and we are unable to effectively measure the actual usage experience of employees. Therefore, in the subsequent empirical analysis, only the two more forward-looking and expectant dimensions of performance expectations and social impact in the UTAUT framework were retained and applied to ensure the validity and situational adaptability of the measurement.

Although TAM and UTAUT have provided a solid theoretical basis for technology adoption research, their explanations for non-technical psychosocial factors and differences in specific application scenarios still have limitations (Venkatesh and Davis, 2000; Legris, Ingham, and Collerette,2003; Williams, Rana and Dwivedi,2015). To address this limitation, this study incorporates three additional variables, equity perception, privacy concerns and social presence, into the UTAUT framework (Özkiziltan and Hassel,2021; Afzal *et al.,* 2023; Benabou and Touhami,2025; Gong *et al.,*2025). This integration aims not only to provide a more comprehensively explanation of employees' willingness to accept AI across different HRM application scenarios and its key influencing factors, but also to validate the applicability of technology acceptance theories in the HR field, offering empirical evidence and practical insights for organizations adopting AI in HRM.

Based on the theoretical foundations above, the following part will describe the research methodology of this study.

5. Research Methods and Research Design

This study adopted a quantitative research method and collected relevant data through a questionnaire. Quantitative methods test the relationships among variables through digital measurement and statistical analysis at the core (Saunders *et al.,*2019). As Creswell (2014) pointed out, quantitative analysis method is suitable for testing theories, determining the relationships between variables, and collecting large amounts of data for statistical analysis. As a standardized data collection tool, combined with cross-sectional design, can efficiently obtain large-scale samples and simultaneously study multiple variables and their interrelationships (Saunders *et al.,* 2008; Bryman and Bell, 2015), to reveal employees' current cognition and attitude towards AI applications.

This study uses a quantitative research method because it allows accurate measurement and verifies the relationships between multiple variables (Saunders *et al.,*2019), which is essential for examining employee's acceptance of AI in different HRM application scenarios and its key influencing factors in this study. The ability of quantitative methods to standardize data collection in larger samples (Saunders *et al.,* 2008; Bryman and Bell,2015) ensured the representativeness and external validity of the study. The cross-section design can quickly reflect the attitudes of employees at specific points in time, meeting the need of this study to exploring the acceptance intentions. Therefore, this method is reasonable and effective choice for achieving the goals of this study and systematically comparing employees' acceptance of AI in different HRM scenarios and its influencing factors.

The questionnaire used in this study will measure employees' willingness to accept and related influencing factors, such as privacy concerns, perception of fairness and social presence. The measurement items of all variables will be based on established Likert scales from existing literature and moderately adapted to fit the specific context of this study to ensure the applicability and effectiveness of the content. The Likert scale has been widely adopted due to its extensive use in measuring attitudes, cognition and behavioural intentions (Bryman and Bell, 2015). The questionnaire can not only maintain the anonymity of participants and enhance the authenticity of their responses (Saunders *et al.,* 2008), but also facilitate the measurement of subjective variables, providing a data foundation for subsequent statistical analysis (Creswell, 2014).

The statistical analysis methods employed are highly consistent with the research questions. Descriptive statistics (Saunders *et al.,*2019) aims to summarize the questionnaire data, which can better understand the distribution of the data and each variable. This directly serves the preliminary exploration of the overall acceptance of employees in this study (the first research question). T-test (Saunders *et al.,*2019) is an inferential statistical method used to compare whether there are significant differences in the means of two samples, to test whether there are significant differences in employees' acceptance of AI in different application scenarios. This is in response to the second research question.

Finally, as the key predictive factors for the affected employees' acceptance of AI, this study will adopt multiple regression analysis. According to the research of Hair (2010), this method can effectively evaluate the independent predictive effect of several predictors of the outcome variable, thereby accurately answering the third question, that is, which factors have a key impact on employees' willingness to accept in different scenarios.

6. Structural Overview

This thesis is divided into five chapters, and the content arrangement of each chapter is as follows:

Chapter One: Introduction

This chapter introduces the research background and motivation, clarifies the research purpose and core questions, discusses the theoretical and practical implications of this study, and summarizes the overall structure of the thesis.

Chapter Two: Literature Review

This chapter systematically reviews the current application status of artificial intelligence in performance management and training development, sorts out the theoretical basis for employees' acceptance of AI, and focuses on analysing the key factors influencing employees' willingness to accept.

Chapter Three: Research Methods

This chapter elaborates on the research design concept, the specific questionnaire construction process, sample selection and data collection methods, and explains the data analysis methods adopted for this study.

Chapter Four: Research Findings and Analysis

This chapter, based on questionnaire survey data, employs multiple statistical analysis methods to systematically reveal the key influencing factors and differences of employees' willingness to accept AI in performance evaluation and training development.

Chapter Five: Discussion and Summary

This chapter mainly conducts a comprehensive discussion on the research results, analyses the influencing mechanism of employees' acceptance of AI in combination with relevant theories, deeply explores the roles of key factors. At the same time, summarize the main research findings, respond to research questions, and propose research limitations and future research directions.

Chapter two——Literature Review

2.1 Introduction

This chapter seek to conduct a systematic analysis of the existing research on the use of artificial intelligence (AI) in human resource management (HRM), focusing on employee acceptance in performance management (PM) and training development (TD) scenarios, and explore influencing factors.

With the popularization and continuous progress of technology, AI is gradually penetrating various functional sections of HRM. Especially in the field of recruitment, the application of AI has achieved rapid popularization and in-depth development (Saad, 2021). Meanwhile, its application in performance evaluation and employee training and development is also gradually becoming increasingly widespread (Bhatt and Muduli,2023; Garg *et al.*,2024).

In the context of the digital labour force, the volume of data also shows rapid growth, and this feature becomes increasingly prominent (George, haas and Pentland,2014). However, Laney (2001) pointed out that the volume, speed and diversity of big data in themselves are not sufficient to support intelligent decision-making. To understand the data more effectively, it becomes crucial to conduct analysis using algorithms. As HRM operations increasingly rely on data-driven approaches, developing and integrating advanced HRM algorithms has become a core task (Ivana,2024). With the aid of algorithm models and data analysis, AI systems can not only enhance organizational performance (Nosratabadi *et al.*,2022), but also effectively prevent potential problems. It shows high potential in improving the efficiency and quality of HR decision-making, especially in efficient and objective performance management (Garg *et al.*,2024), individualized learning recommendations (Ivana,2024), and continuous feedback mechanisms (Garg *et al.*,2024), which are conducive to achieving the optimal allocation of human resources.

To sum up, AI technology is gradually integrating into various functions of HRM. To further understand its practical application, the following will outline the main application areas of AI in HRM management.

2.2 Overview of AI Applications in HR

Research on AI in the HR field can be traced back to 2001. Studies have shown that AI has been used in recruitment and screening processes, such as using neural networks to assist in screening candidates (Marler and Boudreau, 2017; Jatoba *et al.,* 2019). At the end of 2018, research in this field grew rapidly (Gelinas *et al.,* 2022; Jatoba et al.*,* 2019; Gong, Fan, and Bartram,2025). Maghsoudi (2025) conducted a social network analysis and found that the application of AI in HR is gradually expanding, forming diverse research topics. Specifically, the applications of AI cover: strategic planning; Recruitment and deployment; Performance management Training and development Compensation management, employee retention and human relations (Nosratabadi *et al.,*2022; Gryncewicz, Zygaela and Pilch,2023; Ivana,2024; Gong *et al.,*2025; Dayna, Walker and Milan,2025).

Research indicates that performance management and training development, as the core links in human resource management, are directly related to the performance and career growth of employees (Aguinis,2009; Noe,2017). Exploring its acceptance in the context of AI applications is of great significance.

2.2.1 Performance management

AI can utilize the error backpropagation neural network (BP neural network) method to identify high-potential talents, provide data support for talent reserve and succession planning, and integrate multi-source data to construct a comprehensive performance profile to enhance the timeliness and comprehensiveness of evaluation (Zhang and Yuan, 2022; Sampath *et al.,* 2024). Secondly, AI can assist in formulating SMART performance goals based on historical data, employee performance and organizational strategic goals, and integrate 360-degree feedback. Performance Improvement Plan (PIPs) for Mitigating Evaluation Bias Generating Personality (Safitri, Pereira and Patel, 2024, Varma *et al.,* 2024; Sampath *et al.,* 2024).

Furthermore, AI technology can enhance the efficiency and quality of performance feedback, automatically generate personalized feedback reports, reduce supervisor bias, and simulate different feedback scenarios through virtual coaching (Varma *et al.,* 2024;

Sampath *et al.,* 2024). Meanwhile, AI can combine performance data with industry standards to scientifically formulate salary incentive plans, automatically generate improvement plans, enhance the standardization level of communication and employee acceptance, thereby more effectively implementing performance management goals (Varma *et al.,* 2024). Overall, AI demonstrates multi-dimensional values in performance management, including identification, evaluation, development, and improvement, providing a solid foundation for organizations to achieve scientific and personalized talent management.

2.2.2 Training development

Firstly, the AI knowledge graph builds a framework for the knowledge base, visualizes knowledge relationships, and uses knowledge discovery and data mining to identify trends (Liu and Li,2011; Paulheim,2017). Secondly, AI can be combined with natural language processing, data clustering and generative algorithms to accurately assess professional skills and innovation capabilities and thus be applied to training ability diagnosis (Bian, Lu and Li,2022). It can also help new employees understand various aspects of the company's information and become familiar with their positions (Iqbal,2018; Anayat,2023. In addition, by analysing the interactive behaviours of learners, one can gain insights into their understanding levels and learning preferences, thereby optimizing the training content and structure (Luckin and Cukurova,2019; Ruiz-Rojas *et al.,*2023). AI supports employees' self-development and career path planning by monitoring their performance and providing personalized feedback (Maity,2019; Faqihi and Miah, 2023; Kumar *et al.,*2023; Sampath *et al.,* 2024).

Furthermore, AI analysis can effectively identify the training needs of individuals (Jia *et al.,*2018; Sima *et al.,*2020; Chen, 2023). Based on the personal journey and feedback of employees, customise learning content and paths to cultivate soft and hard skills (Morozevich *et al.,*2022; Ma *et al.*,2023). Meanwhile, AI is driving hybrid learning methods and "virtual private mentors" (Chen, 2023; Mitra,2023; Zhang, 2024).

Finally, although PM and TD demonstrate the significant application functions of AI in HR, with the deepening of research, Maghsoudi (2025) revealed through keyword co-occurrence analysis that social science issues such as ethics, fairness, and employee acceptance are becoming emerging focuses of attention, indicating that AI in HRM research is transforming from technology-oriented to human-oriented. Based on this transformation, the potential advantages and challenges of applying AI in HR will be further explored next.

2.3 The potential advantages and challenges of applying AI in HR

In today's rapidly evolving organizational environment, AI technology has demonstrated extensive application potential in the HR field.

Its advantages are mainly reflected in replacing some repetitive tasks to improve efficiency and reduce costs (Duggan *et al.,* 2020; Norlander *et al.,* 2021; Dutta *et al.,* 2023; Bhushan, 2023; Benabou and Touhami, 2025). Enhance employee satisfaction, engagement and organizational identity through personalized experience and communication support (Norlander *et al.,* 2021; Dutta *et al.,* 2023). In recruitment, AI can automate resume screening, accelerate talent matching, and is expected to reduce human bias (Hmoud and Laszlo, 2019; Qamar *et al.,* 2021; Kshetri, 2021; Benabou and Touhami, 2025). In training, AI helps predict future skill requirements and customize learning paths (Saling and Do,2020; Huang, Saleh and Liu,2021; Kim,2022; Ivana,2024; Benabou and Touhami, 2025). In performance management, multi-source data can be integrated to achieve more comprehensive, fairer and more efficient evaluation (Singh and Shaurya, 2021; Sullivan and Wamba,2022; Benabou and Touhami, 2025). In talent retention, data insights are used to identify turnover risks and assist HR departments in optimizing retention strategies (Kshetri, 2021; Bhushan, 2023; Benabou and Touhami, 2025; Gong *et al.,*2025).

However, its application is also accompanied by many challenges, including data quality and bias risk (Ozkiziltan and Hassel,2021; Benabou and Touhami,2025; Gong *et al.,*2025). Lack of emotional understanding and socio-cultural sensitivity (Afzal *et al.,* 2023; Gong *et al.,*2025). Ethics and Privacy Risks (Tambe *et al.,*2019; Sachan *et al.,*2024; Benabou and

Touhami,2025; Gong *et al.,*2025). The decision-making process lacks interpretability (Gelinas *et al.,* 2022; Benabou and Touhami,2025). Therefore, existing studies have emphasized that it is crucial to understand the psychological responses of employees to the integration of AI into HR work. Meanwhile, future studies should explore the behavioural mechanisms of employees' adoption of AI (Tambe *et al.,*2019; Gelinas *et al.,* 2022; Cameron and Rahman,2022; Deng *et al.,*2024; Benabou and Touhami,2025; Gong *et al.,*2025; Maghsoudi *et al.,* 2025).

In summary, AI has demonstrated significant advantages in efficiency and accuracy in multiple aspects of HR, but it also faces many challenges. Next, this article will focus on the overall acceptance of AI in HRM applications by employees and the acceptance in two key scenarios.

2.4 The attitudes of employees towards the application of AI in HR

2.4.1 Overall acceptance attitude by employees

With the in-depth application of artificial intelligence in the field of human resource management, the interaction between employees and technology is becoming increasingly frequent. Therefore, the user experience directly influences satisfaction, and may lead to employees' turnover intentions (Kolatshi, 2017). On the contrary, a good user experience can not only help employees accept AI technology but also may prompt their feedback to drive the optimisation of the system to enhance its functionality, ease of use, and better adapt to the actual operation and needs of the organization (Davis,1989). As the Taslim, Rosnani and Fauzan (2025) Research Institute pointed out, employees' attitudes towards AI technology not only affect the effectiveness of their adoption and use, but also the implementation effect of AI in turn shapes employees' views, forming a continuous feedback and interaction mechanism between the two.

Existing research provides preliminary theoretical and empirical insights into how employees as a whole view the application of artificial intelligence in HR functions. The conclusion of Bhatt and Shah (2023) on employee attitudes indicates that most employees tend to use AI in HRM, but they still hold a cautious attitude towards AI in certain aspects. Oglesby *et al.* (2024) pointed out that employees generally lack trust in the use of AI in key human resource decisions such as recruitment, performance or training. This "AI scepticism" weakens their sense of perceived organisational support (POS), and thereby negatively affects key employee outcomes such as their engagement and retention intentions. The research of Dima *et al.* (2024) further found that although the introduction of AI has significantly improved the efficiency and results of HR activities, the privacy concerns brought about by AI automation continue to weaken employees' trust in it. Moreover, the widespread adoption of AI technology is reshaping the role relationships among HR professionals, employees, and line managers. HR is gradually transforming into an intermediary hub connecting technology and people (Dima et al.,2024). Relevant research supports that HR not only needs to overcome their own resistance and unfamiliarity with AI technology but also should play a crucial bridging and moderating role between employees' cognitive changes and their willingness to adopt technology by establishing employees' trust in the accuracy, reliability and fairness of AI (Arora and Mittal,2024; Dima *et al.,*2024). Dima *et al.* (2024) based on the empirical data of 264 HR practitioners, further pointed out that the cognitive changes brought by employees to AI technology significantly positively influence their willingness to adopt AI (Budhwar *et al.,*2022; Majrashi, 2025).

2.4.2 Acceptance in performance management

In the context of performance management, employees' acceptance of AI shows obvious complexity and trade-offs. Research shows that employees generally believe that fairness is a feature directly related to job performance and can improve the accuracy of predictions (Majrashi,2025). This concern for fairness makes employees more inclined to evaluate AI feedback using fixed formulas, as such feedback is regarded as more objective and neutral (Biswas, Talukder and Khan,2024). However, the research of Biswas *et al.* (2024) pointed out that in situations involving discretionary power and emotional judgment, employees are more inclined to accept feedback from human supervisors to obtain emotional understanding and resonance. It is notable that the way AI combines with humans to provide evaluation, and feedback has gained the highest level of trust and acceptance (Biswas et al., 2024). Although employees acknowledge that the use of AI in performance management evaluation applications has potential to reduce bias and enhance objectivity, they also express concerns about its in impersonality, privacy leakage and other issues, and even question the objectivity and bias reduction that are considered AI's advantages (Park,2021; Varma *et al.,* 2024). Furthermore, some studies have also pointed out that AI systems may weaken the original interpersonal interaction in the workplace, especially the lack of emotional communication and non-verbal understanding between people in performance feedback, thereby weakening employees' trust in AI decision-making (Bankins *et al.,* 2022; Majrashi,2025). This indicates that employees' acceptance of AI performance management is not a single orientation, but is based on multiple trade-offs of technology, emotion and ethics.

2.4.3 Training and development

In the context of training and development, although relevant research is still relatively limited, existing literature shows that employees demonstrate a positive and open attitude towards AI in training and development and generally recognize its potential in supporting personal learning and growth (Kong, 2024; Kochling *et al.,*2025). AI is mostly used as a tool for assisting learning and ability improvement. Therefore, employees pay more attention to whether the AI system can provide emotional support, interactive feedback and a sense of social connection (Wanner *et al.,*2018). Research indicates that employees' positive perception of AI is significantly positively correlated with professional resilience and informal learning behaviours (Kong,2024; Reina-Parrado, Roman-Gravan and Hervas-Gomez,2025) indicates that AI technology plays a positive role in promoting employees' autonomous learning and enhancing their adaptability. The research of Kochling *et al*. (2025) further pointed out that employees generally recognize the practicality of AI in training and development, but at the same time have put forward higher requirements for data sources and process transparency, especially paying attention to privacy risk issues. The research also found that when the decision-making logic and training recommendation mechanism of AI systems are clearly communicated, trust in AI and the willingness to apply it will significantly increase.

Based on the above review of existing research on employees' acceptance of AI in performance management and training development scenarios, it can be initially inferred that there are significant differences in employees' focus on AI systems in different HR scenarios, and such differences may affect the formation mechanism of their acceptance willingness. In performance management, it is directly related to an employee's salary, promotion, bonus and even career development, and carries significant implications for them. Therefore, employees pay more attention to the fairness of their evaluations and the privacy protection of data processing (Biswas *et al.,* 2024; Majrashi,2025). If AI systems lack explanatory mechanisms or transparency, it may intensify concerns about their evaluation and thereby affect their acceptance (Wanner *et al.,*2022).

In conclusion, existing research indicates that employees' acceptance of AI in PM and TD scenarios is mainly influenced by three factors: perception of fairness, privacy concerns, and interpersonal interaction. The following will describe the potential negative impacts of these three factors separately.

Firstly, a sense of unfairness may lead to a decline in job satisfaction (Greenberg,1990; Colquitt *et al.,*2001; Ho, 2025), weakened sense of organizational commitment and loyalty (Meyer and Allen,1997; Cropanzano, Bowen and Gililand,2007; Ho, 2025), this reduces work engagement and develops a negative attitude towards work (Adams,1965; Cohen-Charash and Spector,2001; Ho, 2025), and even lead to resignation (Greenberg,1993; Holtom *et al.,*2008; Golverdi, Sharifirad, and Rastegar,2024) and impaired mental health (Elovainio, Kivimaki and Vahtera,2002; Tepper, 2000; Changaranchola and Samantara,2024).

Secondly, the crossing of privacy boundaries not only triggers moral doubts and public opinion pressure, but also brings management risks (Smith, Milberg and Burke,1996). It can also cause employees to worry, resist and be dissatisfied, leading to loss of trust, anxiety and negative evaluation of the organization (Westin,1967; Smith *et al.,*1996; Lemon *et al.,*2024).

Finally, the lack of interpersonal interaction will affect the employee experience and the acceptance of technology. AI has difficulty providing emotional resonance due to the lack of emotion recognition, non-verbal feedback and context judgment (Bankins *et al.,*2022), and its insufficient sense of social presence limits emotional understanding and motivation perception (Choung *et al.,*2024). Kambur and Akar (2022) pointed out the importance of balancing technology and the human touch in HR.

In conclusion, the perception of fairness, privacy concerns, and the lack of interpersonal interaction affect employees' acceptance of AI in performance management and training development and involve deeper psychological and behavioural mechanisms. To systematically explain these mechanisms and predict employees' willingness to adopt them, it is necessary to analyse them with the aid of a mature technical theoretical framework.

To deeply understand the acceptance behaviour of employees towards the application of new technologies, the two theoretical frameworks, namely the Technology Acceptance Model and the Unified Technology Acceptance and Use Theory, are regarded as the most popular. They are the basic theoretical research models for evaluating the level of technology adoption (Owusu *et al.,* 2022). These models help to reveal the deep-seated reasons why employees hold favourable or opposing attitudes when facing new technologies (Ammenwerth,2019). The following will respectively introduce the core components of these two theoretical models and explore their applicability in AI human resource application scenarios.

2.5 Theories

2.5.1 Technology Acceptance Model (TAM)

TAM was developed by Davis (1989) based on the Theory of Rationed Action (TRA) by Fishbein and Ajzen (1977), proposes that perceived usefulness and perceived ease of use are the key variables influencing an individual's usage attitude and behavioural intention.

This model has received extensive support from multidisciplinary perspectives such as expectancy theory, self-efficacy theory, and innovation adoption research (Davis,1989). Perceived usefulness refers to the user's belief that using the system can significantly enhance their work performance; perceived ease of use, on the other hand, means that the user thinks the system is easy to operate, easy to master, and does not require much effort (Davis,1989). The research conclusion indicates that the main motivation for users to adopt the application lies in the functional value brought by the system, while the simplicity of operation is a secondary factor (Davis,1989). From the perspective of causality, perceived ease of use does not directly affect the decisive factor of system usage behaviour. Instead, it indirectly influences users' willingness to use and actual usage behaviour by enhancing their evaluation of the perceived usefulness of the system, thereby constructing a causal chain from perceived ease of use to perceived usefulness to usage behaviour (Davis,1989).

2.5.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT was proposed by Venkatesh *et al*. (2003) by integrating the elements of eight major models and presenting four core determinants. The performance expectation in its theory refers to the individual's belief that using the system can enhance job performance. Effort expectation refers to the difficulty level of using the system; Social influence refers to the impact that an individual is expected to use a certain technology by others, and its effect is more significant in mandatory use scenarios and early use stages. The facilitating conditions refer to the available organizational and technical support perceived by users, which have a limited impact on behavioural intentions but have a direct promoting effect on the actual use of the system (Venkatesh *et al*.,2003).

The research of Venkatesh *et al*. (2003) shows that although the UTAUT model demonstrates strong explanatory power in predicting the intention of technology usage, it has limitations in depicting how individuals within an organization make specific acceptance and usage decisions. The author also proposed four moderating variables, namely gender, age, voluntariness and experience, which deepened the understanding of individual acceptance. UTAUT provides a guiding framework for management practices, enabling managers to predict the feasibility of technology adoption, identify the key factors affecting user acceptance, and formulate targeted intervention strategies for potential low-acceptance groups to enhance the overall adoption rate of the system (Venkatesh *et al.*,2003).

Overall, TAM focuses on the two key variables of "perceived usefulness" and "perceived ease of use" through a simple and understandable approach, thereby simplifying the evaluation of the complex process of information technology being adopted by individuals. The UTAUT model, based on integrating multiple mainstream theories, systematically introduces four determinants and four moderating variables, making it more comprehensive in explaining user acceptance behaviour and suitable for the analysis of complex environments for technology adoption within organizations. This research will take these two models as the theoretical basis and will be further studied in the preliminary research.

2.5.3 Perception of fairness

To understand more systematically how employees perceive and respond to the issue of fairness, this study will introduce fairness theory and organizational fairness theory to provide a theoretical basis.

1) Equity theory

The equity theory was proposed by Adams (1965), emphasizing that employees will judge whether they are treated fairly by comparing their "input-output ratio" at work with the corresponding ratio of others (Walster *et al.,*1973). This process of social comparison is in line with the core idea of the relative deprivation theory in social psychology (Crosby,1976), that is, after an individual is compared with a reference object, they feel that they have been treated unfairly.

The research also suggests that equity theory is closely related to distributive justice theory. When an individual's input and output are different from those of others, a sense of unfairness may arise (Adams,1965). This further leads to negative emotions such as dissatisfaction and anger in individuals (Adams,1965). Adams (1965) pointed out in his research that the stronger an individual perceives unfairness, the greater the motivation to reduce it. Furthermore, various behavioural and cognitive adjustment strategies may be adopted, including reducing input, increasing returns or withdrawing to terminate the exchange relationship that leads to unfairness (Adams,1965). In conclusion, this theory reveals how individuals perceive and respond to the fairness of distribution through social comparison. However, it focuses on an individual's perception of the outcome and needs to be combined with organizational equity theory to obtain a more comprehensive perspective.

2) Organizational equity theory

The organizational equity theory was proposed by Greenberg (1987). Based on the two dimensions of "reactivity - initiative and process - content", it forms four concepts of equity. Firstly, the reactive content theory, based on the fairness theory (Adams,1965; Represented by Walster *et al.* (1973) and the theory of relative deprivation (Crosby,1976), it mainly focuses on how individuals respond to unfair treatment or unfair resource allocation. Secondly, the proactive content theory, represented by the fair judgment theory (Leventhal,1976,1980a) and the fair motivation theory (Lerner,1977), mainly focuses on how employees actively strive to create a fair outcome distribution. Thirdly, the reactive process theory, mainly referring to the procedural fairness theory (Thibaut and Walker,1975), focuses on how individuals respond to the procedural fairness used for decision-making. Finally, the active process theory, represented by the distributional preference theory (Leventhal, 1980b), explores how individuals strive to create fair procedures and implementations. Overall, this theory systematically clarifies the diversified understanding and behaviour of employees' passive perception and active shaping of organizational equity from results to processes.

In conclusion, compared with the equity theory, the organizational equity theory is more in line with the focus of this study on employees' perception of the fairness of AI systems. Further empirical discussions based on this theory will be conducted in the subsequent preliminary research.

2.5.4 Privacy concerns

1) Communication Privacy Management Theory (CPM)

CPM was proposed by Petronio and Child (2002), which holds that privacy is an individual's perception of ownership and control over their private information. The theory mainly consists of five elements. First, privacy ownership and control: individuals believe they have the ownership and access rights to their own information. Second, the privacy boundary is used to demarcate the line between private and public information and to determine the scope of information flow and management methods. Third, boundary coordination: When an individual decides to share private information with others, the information changes from being exclusively owned by the individual to being jointly owned. Fourth, privacy turmoil refers to the situation where, when individuals make mistakes or fail to coordinate in privacy management, privacy rules are violated, leading to negative impacts. Fifth, privacy rules: Guide privacy management based on the norms set by the information owner. Overall, CPM explains how individuals can manage privacy and its risks by managing information ownership, control rights, and privacy boundaries.

2) Information control theory

The information control theory was proposed by Westin (1967). This theory holds that the essence of privacy is the selective control that individuals have over the collection, use and dissemination of their own information. Research indicates that privacy does not mean that information is completely not shared, but rather that it is up to individuals to decide when, how and to whom to disclose it. By controlling the flow of personal information, individuals can maintain their own boundaries, independence and psychological security. Individuals may have different expectations for information control in different situations. Furthermore, privacy control is closely related to trust. When an organization is perceived as overstepping information boundaries or using data in an opaque manner, individuals' trust will be eroded, thereby triggering negative emotions or behavioural responses. Overall, the information control theory emphasizes that the essence of privacy is an individual's selective control ability over themselves, and this control is crucial for maintaining personal autonomy and psychological security.

4) Privacy regulation theory

The privacy regulation theory was proposed by Altman (1975), and this theory is divided into four core concepts. First, this theory does not regard privacy as information ownership or a closed state but defines it as a continuously regulated process in the interaction between individuals and the social environment (Altman,1975). Second, it is emphasized that privacy is context-dependent and will also be adjusted along with changes in roles, cultures, practices and Spaces (Altman,1975). Thirdly, everyone has a privacy comfort zone. If social contact exceeds their ideal level, individuals will feel disturbed. If it is below the ideal level, one will feel isolated (Altman,1975). At the end, the regulatory mechanism includes both behavioural and cognitive aspects. Individuals will regulate the degree of privacy through behavioural strategies and psychological strategies (Altman,1975).

All in all, the privacy regulation theory regards privacy as a dynamic and context-dependent regulation process, explaining how individuals achieve a balance between actual social contact and the ideal level of privacy through various behavioural and cognitive strategies.

In conclusion, CPM, information control theory and privacy regulation theory reveal the privacy perception and management mechanisms of employees from different perspectives. Given that the systematic interpretation of information boundaries and privacy sharing by CPM is more in line with the specific context of AI application in HRM in this study, the research will take the CPM theory as the theoretical basis of privacy concerns in the initial investigation stage and further conduct empirical discussions.

2.5.5 Lack of human-computer interaction

To understand the insufficient perception of AI interactivity by employees, this study will take social presence as the theoretical basis.

The social presence proposed by Uhl, Neundlinger and Regal (2023) is based on Short's (1976) social presence. The theoretical core consists of four points. First, it refers to the user's perception that they are in the same space or situation as the virtual agent. Secondly, the two-way communication and response capabilities between user perception and virtual agents. Secondly, the degree of immersion, involvement and psychological connection that users experience during their interaction with virtual agents. Finally, virtual agents can simulate human behaviours and communication cues. The research also pointed out that the two dimensions of social presence, namely comprehension and behavioural independence, were moderately positively correlated with recognition. This means that when social presence is low, participants' recognition of training may also decrease, and learners may reduce their engagement, thereby possibly having a negative impact on long-term learning outcomes (Uhl *et al*.,2023).

Overall, Uhl *et al*. (2023) concretized the core of social presence as the sense of coexistence between users and virtual entities, interactive response capabilities, psychological participation, and the ability of agents to simulate human behaviours and communicate cues. In view of this, this study will further explore the factors of the lack of interpersonal interaction in the application of AI in HRM in the preliminary research.

2.6 Literature review summary

This review systematically sorts out the existing literature, aiming to deeply explore the application of artificial intelligence in the field of human resource management and its impact on employee acceptance. A review of existing research indicates that AI technology is increasingly penetrating all aspects of HRM, gradually expanding from the early recruitment screening to multiple modules such as performance management, talent development, and employee relations (Nosratabadi *et al*.,2022; Gryncewicz, Zygała and Pilch,2023; Ivana,2024; Gong *et al*.,2025; Dayna, Walker and Milan,2025). The application of AI in HRM undoubtedly brings significant advantages, such as greatly improving the operational efficiency and decision-making quality of HR (Kshetri, 2021; Benabou and Touhami, 2025; Gong *et al*.,2025). However, existing studies have also generally revealed the complexity of employees' acceptance of the application of AI in HRM (Varma *et al*.,2024; Kochling *et al*.,2025; Gong *et al*.,2025; Benabou and Touhami,2025).

As mentioned in the previous section on "Employees' Acceptance of Performance Management and Training Development", existing research has preliminarily revealed that employees core concerns regarding AI systems differ significantly between the two different HR contexts of performance management and training development. This difference is manifested as follows: In the context of performance management, due to its highly significant relationship, employees place more emphasis on fairness and data privacy protection. In the training and development scenario, the focus is more on whether AI can interact and provide feedback as well as the necessary sense of social connection. This indicates factors such as perception of fairness, privacy concerns, and social presence may have significant differences in the relative importance and action paths of employee acceptance in different HR situations

Therefore, the core point of this review lies in emphasizing that although AI technology has brought unprecedented improvements in efficiency and accuracy to HRM, the psychological acceptance of employees is the key to its successful implementation and long-term effectiveness. This kind of acceptance is not only complex, but also comprehensively influenced by multiple complex factors of perception of fairness, privacy concerns and the lack of interpersonal interaction. Understanding these key influencing factors and their specific mechanisms of action in different HR scenarios is crucial for enterprises to effectively deploy and manage AI.

2.7 Research gap and research value

Although the research on AI in HRM is showing growth (Abu *et al.*,2024), the current AI in HRM literature is mostly concentrated in the field of computer science and engineering, and the academic participation in the HR field is still relatively limited (Jatoba *et al.*,2019; Maghsoudi *et al.*,2025). This unbalanced disciplinary structure further highlights the need for interdisciplinary collaboration. Maghsoudi *et al*. (2025) call on HR researchers to actively engage in AI-related research agendas, constructing more adaptive theoretical frameworks from perspectives such as organizational behaviour, employee experience, and institutional design, thereby filling existing knowledge gaps.

More importantly, there is a lack of research in the existing literature that systematically compares the differences in employee acceptance in different AI application scenarios from the perspective of employees. Especially in the two representative and contrasting application scenarios of performance management and training development, the differences in employees' psychological responses and acceptance levels have not received sufficient attention. Furthermore, the relevant research pages lack a systematic theoretical framework and cross-scenario empirical analysis.

To fill this gap, this study focuses on two key application scenarios in performance management and training development, delving into the impact of psychological factors such as privacy concerns, perception of fairness, and lack of interpersonal interaction with AI technology on employees' acceptance of AI. The aim is to expand the application scope of the existing technology acceptance model in the field of HR management through empirical data, and to provide a basis for filling the research gap in the comparison of employees' behavioural intentions and psychological acceptance of support in these two application scenarios.

It also provides theoretical basis and practical reference for organizations to support the formulation of more targeted and inclusive AI implementation strategies, this will promote the effective application of AI in HRM, enhancing employee acceptance, and responding to the "people-oriented" management needs of enterprises.

Chapter three——Research Methodology

3.1 Introduction

This chapter introduces the research design and methodologies of the study. Research methodology is a systematic process of solving research problems through scientific procedures and steps, emphasizing logic and consistency throughout the entire research process (Chaturvedi, 2023). Given that this study aims to explore employees' acceptance of artificial intelligence (AI) in performance management (PM) and training development (TD) and the differences among them, a quantitative research method is adopted. As there are still few comparative studies of this kind in the existing literature, this research adopts an exploratory approach without making assumptions and summarizes valuable insights from the data. This chapter will successively introduce the research purpose and questions, research framework, research concept, research methodology and methods, data collection methods, sample selection, data presentation and analysis methods, ethical considerations, and research limitations, to ensure the reliability and validity of the research.

3.2 Research Aim

This study aims to systematically explore employees' acceptance of the application of AI in HRM, with a focus on two typical application scenarios PM and TD. By comparing the attitudes of employees in these two specific situations, the study aims to identify whether there are significant differences in their acceptance. In addition, the study focuses on the relative influence of three key factors: privacy concerns, perception of fairness, and lack of interpersonal interaction in employees' willingness to accept different applications. The research aims not only to understand the overall acceptance of employee AI in HRM applications, but also to reveal how these psychological factors function in different contexts.

Based on the above research purposes, the main objective of this study is:

1) Do employees remain open to the potential use of AI in HR applications?

2) In the application scenarios of artificial intelligence for PM and TD, which one do employees tend to accept more?
3) In the two application scenarios of PM and TD, the factors of privacy concerns, perceptions of fairness, and lack of interpersonal interaction, which one is most significant?

3.3 Research Frameworks

The research framework of this study is based on the research onion model proposed by Saunders, Lewis, and Thornhill (2019), which compares the research process to peeling an onion, with each layer corresponding to a key decision in the research design. Next, starting from the outermost research philosophy, we will gradually refine the research design elements inward layer by layer.

The outermost layer is research philosophy, which reflects the researcher's basic assumptions about knowledge and development and serves as the foundation of research design. This study choses a positivist philosophy, emphasizing the existence of objective reality and discovering laws through the methods of systems science (Saunders *et al.,*2019).

The second layer is the research methodology path, namely the deductive method and the inductive method. This study uses induction to summarize patterns, trends and new insights from specific data (Saunders *et al.,*2019).

The third layer is research selection, namely the selection of data types (Saunders *et al.,*2019). This study adopts a single data type.

The fourth layer is the research strategy, that is, the path to collect and analyse data (Saunders *et al.,*2019). This study collected quantitative standardized data through structured questionnaires.

The fifth layer is the temporal perspective, namely longitudinal study or cross-sectional study (Saunders *et al.,*2019). This study is a cross-sectional study, and data were collected at specific time points.

The sixth layer is data collection and data analysis. This study mainly uses self-administered questionnaires to collect data through an online platform and employs statistical methods for data analysis.

Through the hierarchical design of the onion model, the consistency of decision-making and logic at each layer and the internal coherence are ensured, providing theoretical and methodological support for achieving the research purpose (Saunders *et al.,*2019).

3.4 Research philosophy

This study adopts positivist philosophy. This philosophy emphasizes the study of social phenomena through observable and measurable data systems, reveals the regular connections among variables, and requires researchers to remain neutral and objective in the process and avoid subjective judgments affecting the research results (Saunders *et al.,*2019).

Other research philosophical positions include interpretivism, critical realism and pragmatism, each of which has its own advantages (Saunders *et al.,*2019). Interpretivism focuses on subjective experience and social significance and is suitable for qualitative exploration and in-depth interpretation of individual behaviour (Saunders *et al.,*2019); Critical realism focuses on deep mechanisms and emphasizes theoretical construction and complex causality (Saunders *et al.,*2019); Pragmatism emphasizes problem-oriented research and flexible selection of multiple methods (Saunders *et al.,*2019). However, given that this study aims to collect and analyse quantifiable data, test variable relationships, and pursue objective and verifiable patterns, positivism best aligns with the research objectives and methodology of this study.

Specifically, the aim of this study is to explore and identify the differences in employees' acceptance of the application of AI technology in HRM, and to derive more general cognitive patterns. This is consistent with the pursuit of objective laws by positivism (Saunders *et al.,*2019). The study collected data using standardized questionnaires and Likert scales to operationalise the psychological constructs at the individual level into measurable values (Bryman and Bell,2015), ensuring a systematicity, comparable and repeatable approach (Saunders *et al.,*2019). Finally, this study summarizes representative and universal conclusions from the sample data, reflecting the applicability and guiding significance of maintaining neutral and objective in research design under the positivist paradigm (Saunders *et al.,*2019).

3.5 Research approach and strategy

This study adopts the inductive method. This method is a reasoning process that starts from specific facts, observations or experiences to deduce universal laws or conclusions. This study starts from the questionnaire response data of on-the-job employees, summarizes and identifies the perception dimensions and potential structures of employees in the scenarios of AI application in PM and TD. Although some variables of TAM and UTAUT were referred to, the research focus was not on testing the presuppositions of falsies, but on summarizing universal cognitive patterns from the data to provide a reference based on real perception of the introduction of AI in organizations.

Other reasoning methods include deduction and abductive reasoning. The deductive method relies on existing theories to propose hypotheses and then verify them through data (Saunders *et al.,*2019). Abductive reasoning combines inductive and deductive methods to provide reasonable theoretical explanations in the observation of facts (Suddaby,2006; Saunders *et al.,*2019). However, this research field is still in the early stage of theoretical construction, and related studies are relatively limited. If the deductive method is used, the complexity and diversity of employees' real perception may be ignored. Therefore, starting from the specific perceived data, this study summarizes universal cognitive patterns, providing organizations with insights and decision-making references based on real perception before introducing AI into HRM practices.

In addition, this study adopts an exploratory research design. Due to the current lack of systematic exploration in the academic community regarding the application of AI, especially in the employee acceptance and perception mechanisms in PM and TD contexts (Jatoba, M. et al. 2019; Maghsoudi et al. 2025). Maghsoudi et al. have called on HR researchers to construct a more adaptive local theoretical framework from the perspectives of organizational behaviour, employee experience, and system design to fill this gap. In this field where theory is still not mature, deductive methods are difficult to fully capture the complexity of phenomena. Therefore, this study adopts a data-driven induction method to deeply explore and identify the relative mechanisms of the acceptance differences and key influencing factors of employees in the two scenarios. As Locke (2007) pointed out, the construction of inductive theories in fields lacking mature theories is crucial for the progress of social sciences. Although this study drew on some variables from TAM and UTAUT, no hypothesis testing was conducted, and the research approach still mainly adopted the inductive method.

3.6 Data collection approach

This study employs quantitative research methods. This method examines the relationship between variables through digital measurement and statistical techniques (Saunders *et al.,*2019) and is applicable to the relationship between the acceptance degree of employees' application of AI in HRM and the key influencing factors in this study. Quantitative methods can systematically analyse the correlations among variables and generalize the conclusions (Saunders *et al.,*2019), which is in line with the goal of this study to explore influence patterns and statistical significance.

This study also considered qualitative and mixed methods. Qualitative research emphasizes understanding individual subjective experience and social significance and is applicable to research that emphasizes context and details (Saunders *et al.,*2019) but does not conform to the focus of this study on different influence patterns and statistical significance. Although the hybrid method can combine quantity and quality, its design is complex and the resource input is large (Saunders *et al.,*2019), which does not meet the feasibility of this study in terms of time and resources. Therefore, considering the nature of the research question, data requirements, and analysis objectives comprehensively, quantitative methods can most effectively support the goals of this study, namely the systematic analysis of variable relationships and theoretical generalization.

Data collection was conducted using a structured questionnaire and measured with the Likert five-point scale, which facilitated standardization and statistical analysis. The questionnaire design referred to several widely validated mature scales (Bryman and Bell,2015), and pre-tests were conducted to improve reliability and validity (Saunders *et al.,*2019). Questionnaire surveys can efficiently obtain data in large-scale samples, ensuring the representativeness and comprehensiveness of the research (Saunders *et al.,*2019).

This research is based on positivist philosophy and investigation research strategies. Emphasize the discovery of patterns through observable and measurable data and ensure the objectivity of data and reduce researcher bias through standardized questionnaires and statistical analysis (Saunders *et al.,*2019). Although quantitative research is often associated with deductive methods to test existing theories, it is also allowed to combine inductive methods to develop or clarify theories through data (Saunders *et al.,*2019). In the preliminary analysis of this study, potential dimensions were explored, demonstrating the characteristics of inductive exploration in quantitative research. Probability sampling was adopted as much as possible to enhance the representativeness of the sample and ensure the generalizability of the conclusion.

3.7 Data collection method

This study used structured questionnaires to collect core data and effectively capture complex psychological phenomena in a quantitative way (Bryman and Bell,2015). The variables of concern include employees' acceptance of AI, perceived usefulness, ease of use, fairness, privacy concerns and interpersonal interaction. These are all subjective psychological constructs at the individual level, and their abstract characteristics are difficult to measure through direct observation or physical methods (Davis,1989; Venkatesh *et al.,*2003; Bryman and Bell,2015). Relevant studies have shown that transforming theoretical concepts into quantifiable specific statements and measuring them through standardized, self-presenting structured questionnaires can ensure the consistency and repeatability of data collection and obtain standardized information of large samples at high efficiency, laying the foundation for subsequent analysis (Davis,1989; Venkatesh *et al.,*2003; Bryman and Bell,2015).

The research design also considered interviews and focus groups. Although interviews can deeply understand an individual's subjective experience, qualitative data is not conducive to statistical analysis among variables, the sample size is limited, and it is easily influenced by the guidance of researchers (Bryman and Bell,2015; Creswell and Poth,2016; Saunders *et al.,*2019). Although focus groups can stimulate viewpoints through interaction and are suitable for exploratory research, it is difficult to extract standardized variables, and the group environment may suppress the true expression of respondents on sensitive issues (Morgan, 1997; Krueger,2014; Saunders *et al.,*2019). Therefore, neither of them met the requirements of objectivity and large sample data in this study. Eventually, the questionnaire survey method was adopted.

The questionnaire adopts the five-point Likert scale, setting five levels from "strongly disagree" to "strongly agree" to quantify the respondents' attitudes and subtle differences (Likert,1932). This scale can effectively transform subjective psychological experiences into quantifiable continuous data and is applicable to various statistical methods (Likert,1932; Trochim and Donnelly,2001; Jamieson,2004). The questionnaire design referred to multiple validated mature scales and made necessary contextualized adjustments in combination with the specific context of the application of AI in HRM to ensure reliability and validity. To improve data quality, the questionnaire provides brief explanations when it involves both PM and TD application scenarios.

The questionnaire is divided into three parts: The first part (Q1-Q3) collects background information. The second part measures acceptance and acceptance comparison based on the TAM theory (Davis,1989), and (Q4-Q5) measures acceptance based on perceived usefulness and perceived ease of use. (Q6-Q7) Comparison of acceptance between the two applications. Part Three, further measure the key influencing factors (Q8-Q9, Q16-Q17) based on the influence of performance expectations and social impact (Venkatesh *et al.,*2003) on acceptance in UTAUT. Privacy concerns (Q10-Q11, Q18-Q19) are based on the CPM theory (Petronio and Child,2002) to capture respondents' perceptions regarding personal data security. Equity perception (Q12-Q13, Q20-Q21) is based on organizational equity (Adams,1965; Greenberg,1987) Perception of outcome fairness and process transparency. Interpersonal interaction (Q14-Q15, Q22-Q23) is based on the social presence theory (Uhl *et al.,*2023) on the perception of communication opportunities with humans, substitutability of interpersonal interaction, as well as learning atmosphere and sense of belonging.

Due to the sampling method of this study, it is impossible to ensure that all respondents have experience in applying AI in HRM, and other elements in UTAUT that depend on actual usage scenarios (such as effort expectations, facilitation conditions, etc.) are included.

This standardized and mature measurement design can obtain quantitative data with high reliability and validity, ensuring the systematic and standardised of the measurement, laying the foundation for exploratory analysis (Bryman and Bell and Bell,2015), thereby revealing the potential cognitive dimensions and structure of employees regarding the application of AI in HRM, and providing theoretical support for organizational practices.

3.8 Questionnaire piloting

The purpose of the pre-test is to optimize the questionnaire to ensure the smoothness of the entire survey process (Saunders *et al.,*2019). Meanwhile, the preliminary analysis of the pre-test data can ensure that the collected data can answer the research questions (Saunders *et al*.,2019). Before the questionnaire was officially distributed, the study conducted a questionnaire pre-test on five employed people aiming to assess the clarity of the questionnaire items, the consistency of understanding and the overall structure arrangement. Participants provided feedback and suggestions on obvious wording issues and ambiguities, their understanding of the application of AI in the two scenarios of performance management and training development, the logic of the answers, and the filling time.

Based on the feedback, the research has revised some unclear or ambiguous issues and added explanations at the top of the topic pages of the PM and TD scenarios to facilitate better understanding. In addition, the sequence and logical basis of the questions have been adjusted according to the feedback. Although the test sample is relatively small and may not cover all potential issues, as an initial test, this step plays a crucial role in optimizing the language expression and logical flow of the questionnaire.

3.9 Sampling

This study employs non-probability sampling, and probability sampling is also commonly used (Creswell,2014; Saunders *et al.,*2019).

Probability sampling gives each unit in the population a known and non-zero chance of selection through random means, making the sample available for statistical inference and generalization (Saunders *et al.,*2019). Common types include simple random sampling (where each unit has an equal probability of selection), systematic sampling (sampling according to certain rules), stratified sampling (stratifying the population by characteristics and sampling proportionally), and cluster sampling (dividing the population into group owners and randomly selecting the entire group) (Saunders *et al.,*2019).

Non-probability sampling refers to the situation where not every individual can be selected. Therefore, the results are difficult to generalize but are suitable for in-depth analysis of specific groups (Saunders *et al.,*2019). Its common types include convenience sampling (selecting accessible samples), judgment sampling (researchers subjectively select samples based on research purposes and experience), quota sampling (like stratified sampling, but the selection of samples is not random), and snowball sampling (initial investigators recommend other subjects) (Saunders *et al.,*2019).

This study aims to examine employees' acceptance of the application of artificial intelligence in human resource management and its influencing factors. To gain diverse perspectives and cover a wide range of groups, the study combined judgment sampling with snowball sampling and expanded the sample sources through social networks. Specifically, the questionnaire was released through the Google Survey and WJX online platforms. The initial sample was drawn from the professional networks of researchers and then expanded to include more employees from various industries and backgrounds based on their acquaintances with full-time or part-time experience, thereby strengthening the realistic basis of the research.

3.10 Data Presentation and Analysis

This study collects quantitative data through structured questionnaires and will present it in the form of descriptive statistical tables, pictures and textual explanations to visually reflect employees' acceptance attitudes towards the application of AI in HRM and related influencing factors.

Data analysis will combine descriptive statistics and inferential statistics to conduct in-depth analysis for different research questions.

Research Question 1: Descriptive statistical methods (Saunders *et al.,*2019) were adopted to summarize the overall attitude of employees towards the application of AI in HRM, and two-factor repeated measures analysis of variance was conducted with age as the independent variable to explore the potential influence and interaction effect of age on attitude.

Research Question 2: The paired sample t-test in integrative statistics (Saunders *et al.,*2019) was used to compare the differences in acceptance of the same respondent in two application scenarios. Meanwhile, a two-factor repeated measures analysis of variance was conducted with age as the independent variable.

Research Question 3: Multiple linear regression analysis (Saunders *et al.,*2019) was adopted to examine the independent influence of multiple factors on employees' acceptance of AI and quantify the intensity of each factor's effect.

All data analyses were conducted using SPSS software. This software is widely used in social science research and can efficiently perform operations such as data management, transformation and statistics, which helps ensure the systematisms and accuracy of data analysis and other aspects.

3.11 Ethical Considerations

Research ethics is a moral code that every researcher must abide by, aiming to protect the rights and interests of respondents while maintaining the scientific nature and credibility of research (Saunders *et al.,*2019). This study strictly adheres to informed consent, voluntary participation, confidentiality and anonymity, avoidance of harm, and data protection, etc. (Zikmund, 2002; Saunders *et al.,*2019).

1) Informed consent.

The first page of the questionnaire explains the research purpose, the required time, the involved content and the voluntary nature of participation. The respondents were clearly informed of their right to suspend and withdraw at any time. And the right to know about the methods of data collection and use.

2) Voluntary.

All participation is voluntary, and no form of pressure or negative consequences will be suffered for participating or refusing to participate.

4) Anonymity and confidentiality.

Through online data collection, no identifiable recipient information is designed. All data is anonymized and cannot be traced back to individuals, thus ensuring the privacy of participants.

4) Avoid harm.

During the design and implementation of the questionnaire, the possible psychological or emotional impacts on the participants were fully considered. The content was repeatedly reviewed and tested to avoid bias or sensitive issues and ensure that the expression was neutral and objective.

5) Data protection.

The original data is encrypted and stored in password-protected electronic devices, accessible only to research members. After the research is completed, it shall be filed or deleted in accordance with ethical regulations. The report is presented only in a summary form and does not involve any information that can identify individuals.

3.12 Limitations

Although this study strived for rigour in the design and implementation process, there are still some limitations that cannot be ignored. Firstly, the research data relies on self-reports obtained from questionnaires and may be influenced by social expectation biases or subjective judgments. Secondly, the samples are mainly obtained through judgment sampling combined with snowball sampling, with limited industry and regional distribution, which affects the representativeness and generalization of the results. Thirdly, by adopting a cross-sectional study design and collecting data at only a single time point, it is impossible to reflect the changes in employees' attitudes towards the application of AI in HRM or the causal relationship between inferred variables. Fourth, although the questionnaire design referred to existing mature scales and had a certain basis of reliability and validity, some variables still had strong subjectivity and situational dependence. Relying solely on quantitative data might be difficult to fully understand the true feelings and motivations of the respondents. Finally, this study focused on the subjective perception of employees and did not directly measure the usage behaviour or performance outcomes of AI in HRM. Furthermore, this study focuses on exploration and does not propose hypotheses based on specific theoretical models, which may have relatively limited explanatory power.

3.13 Conclusion

This chapter systematically expounds the design and implementation methods of this research. Based on the positivist philosophical stance, this research explores and summarizes employees' attitudes towards the application of AI in HRM and its influencing factors through objective and quantifiable data. By adopting inductive methods and exploratory research designs, the aim is to discover new insights from the collection and analysis of data. The data was collected through a cross-sectional structured questionnaire survey, which drew on mature scales such as TAM and UTAUT, and described the specific application scenarios of AI in performance management and training development to ensure the accuracy of the measurement and the understanding of the respondents. The study employed judgment sampling and snowball sampling in non-probability sampling to obtain a diverse and widely covered sample. Data analysis combines descriptive statistics and inferential statistics. The analysis was conducted using SPSS software. Before the analysis, data cleaning was carried out, including eliminating invalid questionnaires, handling outliers, and unifying variable coding, etc., to ensure data quality.

The research strictly adheres to ethical norms, including informed consent, voluntary participation, anonymity and confidentiality, avoidance of harm, and data protection, among other moral principles, to safeguard the rights and interests of participants. Despite certain limitations in aspects such as sampling methods, cross-sectional design, the questionnaire method itself, and the exploratory nature, this study still strives to provide valuable preliminary insights for the research and practice of AI in the field of HRM through rigorous methods.

Chapter four——Findings and Analysis

4.1Introduction

This chapter presents the key data and analysis results of this study, aiming to reveal employees' acceptance of the application of AI in HRM and the differences in various scenarios.

The research focuses on two typical scenarios of performance management (PM) and training and development (TD), outlining the overall acceptance of employees towards the application of AI in HRM, and comparing the acceptance attitudes of employees in these two situations. The research also analyses the influence of three key factors, privacy concerns, perception of fairness and lack of interpersonal interaction on acceptance.

The analysis is centred around the following research questions:

1. Do employees remain open to the potential use of artificial intelligence in HR applications?
2. In the application scenarios of artificial intelligence for performance management evaluation and training development, which one do employees tend to accept more?
3. In the two application scenarios of performance management evaluation and training development, among the three factors of privacy concerns, fairness perception, and lack of interpersonal interaction, which one most significantly affects employees' acceptance of AI?

To effectively answer the above questions, the structure of this chapter is as follows. The first part introduces the demographic characteristics of the respondents. The second part is the descriptive analysis of the overall data. The third part presents the empirical analysis and results of the research question. The fourth part is the discussion of the results.

4.2 Demographic characteristics

The basic demographic characteristics of the participants not only contribute to understanding the representativeness of the sample composition, but also provide an important basis for data analysis, interpretation and conclusion (Saunders *et al.*,2019).

A total of 89 valid questionnaires were collected in this study, covering age, industry, and the use of AI in HRM by the respective companies.

1) Age distribution

The age distribution is shown in Figure 1. The sample is mainly composed of young people. 88.7% of the respondents are under 40 years old, among which 49.4% are 18-29 years old, 39.3% are 30-39 years old, 9% are 40-49 years old and 2.2% are 50 years old and above.

Table 1: Frequency distribution of participants by age

Age_Group	n	% of sample
18-29	44	49.40%
30-39	35	39.30%
40-49	8	9%
50 or above	2	2.20%
Total	89	100%

2) Industry distribution

The industry distribution is shown in Table 2. The respondents mainly come from sales/marketing/advertising (21.3%), education/training (15.7%), services (12.4%), and information technology and (IT)/software development (11.2%). Respondents from other industries accounted for a relatively low proportion of 10%. But overall, it shows a certain degree of diversity.

Table 2: *Frequency distribution of participants by a job sector*

Job Sector	n	%
Sales / Marketing / Advertising	19	21.30%
Education / Training	14	15.70%
Service Industry (Food & Beverage, Tourism, Hospitality, etc.)	11	12.40%

Information Technology (IT) / Software Development	10	11.20%
Other sectors	35	39.2%
Total	89	100%

Note. Other sectors include Finance / Banking / Insurance, Healthcare / Medical / Nursing, Culture / Media / Entertainment, Construction / Real Estate, Government / Public Administration, Manufacturing / Industrial Production, Energy / Utilities, Agriculture / Forestry / Fisheries, Transportation / Logistics / Warehousing, and Legal / Consulting each accounting for less than 10% of the sample

3) Does the company use AI in HRM

The application of AI in companies is shown in Table 3. 50.6% of the respondents indicated that their companies have used AI in HRM, 29.2% clearly stated that they have not yet used it, and the rest could not confirm the relevant information. This indicates that the application of AI in HRM in the sample has achieved a certain degree of popularity.

Table 3: *AI Usage in HRM by Samples' Companies*

AI Use in HRM	n	%
Yes	45	50.60%
No	26	29.2%%
Not Sure	18	20.2%%
Total	89	100.00%

4.3 Descriptive analysis of the overall data

This section provides a preliminary descriptive analysis of the core variables (see Table 4). All variables were measured using the Likert five-point scale (1= strongly disagree, 5= strongly agree).

In PM, respondents had the strongest perception of a lack of interpersonal interaction (mean =4.01), reflecting a widespread concern about the reduction in interpersonal communication. This is consistent with the conclusion that research indicates that AI systems may weaken emotional communication and non-verbal understanding in scenarios such as performance feedback, affecting employees' trust in AI decisions (Bankins *et al.,* 2022; Majrashi,2025). The second concern is data collection (average =3.92). This is consistent with the conclusion in the literature that while employees recognize the advantages of AI, they also express a high degree of concern about dehumanization tendencies and data privacy risk tables (Park,2021; Varma *et al.,* 2024).

In TD, the average value of the learning atmosphere and interpersonal interaction is 3.91, indicating that employee acceptance is jointly influenced by interactivity and the learning environment. This is consistent with the view in the existing literature that employees generally hold an open attitude towards the application of TD, recognize its potential for individual learning and growth, and expect it to provide personalized learning suggestions while enhancing the interactivity and experience of training (Wanner *et al.,*2018; Kong, 2024; Kochling *et al.,*2025).

Efficiency improvement was highly recognized in both scenarios (PM=3.89, TD=3.80). This indicates that respondents generally believe that AI plays a role in promoting efficiency in PM and TD. This is consistent with the view in the literature review that the application of AI in HRM has indeed significantly improved organizational operational efficiency and decision-making quality (Kshetri, 2021; Bhushan, 2023; Benabou and Touhami, 2025; Gong *et al.,*2025).

In contrast, the PM assessment score for fairness was the lowest (average PM =3.36), indicating that employees have concerns in this aspect. This is consistent with the conclusion in the literature that one of the most core challenges of AI in the HRM scenario is the concern of employees about its lack of fairness (Sachan *et al.,*2024).

Table 4: Means and Standard deviations of Main Variable(N=89)

Variable	Mean	Std. Deviation
PM Lacks interaction (II)	4.1	0.867
PM Data collection concern (CPM)	3.92	0.772
TD Lacks learning atmosphere (II)	3.91	0.913
TD Lacks interaction (II)	3.91	0.887
PM efficiency (PE)	3.89	0.775
TD Data leakage risk (CPM)	3.85	0.806
TD efficiency (PE)	3.8	0.726
TD Data collection concern (CPM)	3.79	0.79
PM Data leakage risk (CPM)	3.78	0.876
Company support TD (SI)	3.74	0.86
Company support PM (SI)	3.67	0.836
PM Reduce communication with colleagues (II)	3.61	1.04
TD Transparent recommendations (POJ)	3.6	0.926

PM Evaluation transparency (POJ)	3.53	0.88
TD Fair recommendations (POJ)	3.51	1.001
PM Evaluation fair (POJ)	3.36	0.908

Note. POJ= Perceived Organization Justice; CPM= Communication Privacy Management Theory; II= Interpersonal Interaction; SI= Social Influence; PE=Performance Expectancy.

Overall, employees generally pay attention to the reduced interpersonal interaction and data privacy issues brought about by AI applications and recognize its advantages in efficiency improvement. However, they are relatively reserved about the fairness of PMS. The standard deviations of each variable are concentrated between 0.7 and 1.0. Although there are individual differences, the overall trend consistency is relatively high, enhancing the stability and representativeness of the results.

4.4 Empirical analysis and results of the research question

Question 1, Do employees remain open to the potential use of artificial intelligence in HR applications?

To explore whether employees are open to the potential use of AI in HRM. This study constructed the “Openness_AI” variable as the core measurement metric. This variable is based on two 5-point Likert scale questions, respectively measuring the perceived usefulness and perceived ease of use of employees regarding the application of AI in HRM. Add up the scores of the two questions and take the average to get a theoretical range of 1 to 5 points. The higher the score, the more positive the open attitude. There are no missing values in the sample.

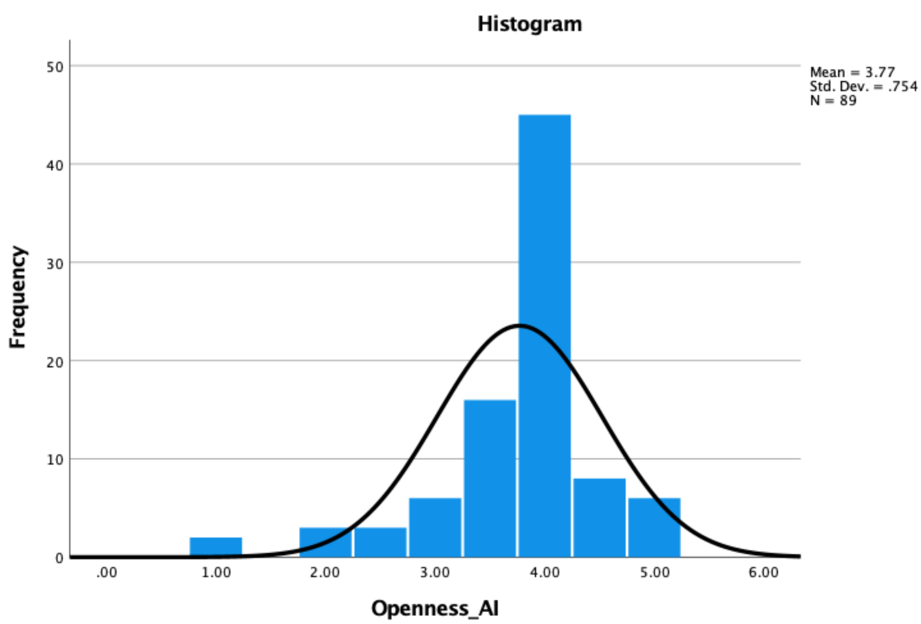
Table 5 and Figure 1 show that the average score of employees on “Openness_AI” is 3.77 (SD=0.75), with a median and mode of 4. It indicates that most employees tend to agree or strongly agree with the relevant statements, reflecting a generally positive attitude. In addition, the negative skewness of 1.45 and the positive kurtosis of 3.416 indicate that the distribution is concentrated in the high-score range, reinforcing the conclusion that the overall attitude is open. This finding is consistent with the research of Bhatt and Shah (2023), supporting that employees generally hold a high degree of openness towards the application of AI in HRM.

Table 5: Descriptive statistics of the "Openness_AI" variable

Statistic	Value
n	89
Mean	3.7697
Median	4
Mode	4
SD	0.75399
Skewness	-1.45
Kurtosis	3.416

Note. SD=Std. Deviation.

Figure 1. Histogram of the "Openness_A"I variable



To explore the differences in "Openness_AI" among different age groups, the sample distribution was 18-29 (n= 44), 30-39(n=35), 40-49(n=8), and 50 and above (n=2).

As shown in Table 6, in the 18-29 and 30-39 age groups with relatively abundant samples, the mean openness was 3.83 and 3.64 respectively, and the median was 4 for both. The box plot (Figure 2) shows that the scores of the two groups are mainly concentrated in the higher score range, but both have low separation groups, indicating that while the overall attitude is positive, there are still some employees holding reserved or even negative views. The 40-49 age group (mean 3.88) and those aged 50 and above (mean 4.25) were only presented as exploratory findings due to the small sample size. Although the mean value of the group aged 50 and above was the highest at 4.25, there were only two samples, which did not have statistical significance. However, it can be used as a reference for expanding the sample size in future studies.

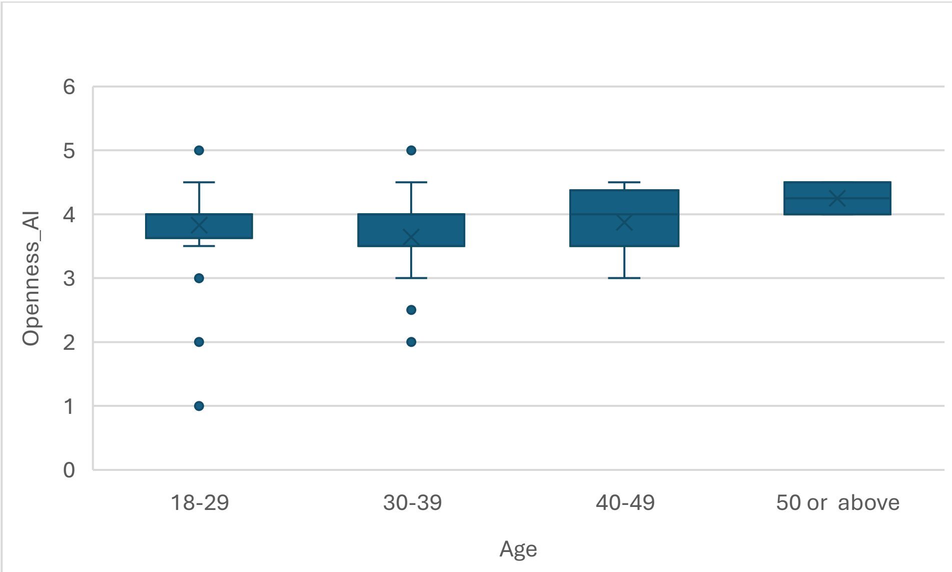
The standard deviations of each age group range from 0.35 to 0.84, indicating that although there are individual differences, the overall trend is relatively consistent. Although the age factor has not been widely explored in the existing research on the acceptance of AI in HRM, the preliminary results of this study suggest that age may affect openness, providing a new perspective and the possibility of theoretical expansion for future related research.

Table 6. Descriptive Statistics of “Openness_AI” by Age Group

Age_Group	n	Mean	Median	SD	Min	Max
18-29	44	3.83	4	0.84	1	5
30-39	35	3.65	4	0.70	1	5
40-49	8	3.87	4	0.52	1	5
50 or above	2	4.25	4.25	0.35	1	5

Note. SD=Std. Deviation; Min=Minimum; Max=Maximum.

Figure 2. Box Plot of “Openness_AI” by Age Group



Question 2, In the application scenarios of AI for PM and TD, which one do employees tend to accept more?

To compare the differences in employees' acceptance in different HR scenarios, this study conducted a paired sample t-test on "Performance management acceptance" (Postitive_PM) and "training and development acceptance" (Postitive_TD).

The descriptive statistics results (see Table 7) show that the average acceptance of TD is 3.92, slightly higher than that of PM, which is 3.78. There is a significant positive correlation between the two, indicating that employees' overall attitudes are consistent in the two scenarios, but their tendency towards TD is slightly higher. This trend is consistent with existing research, and employees generally recognize the learning role of AI in training development (Kong, 2024; Kochling *et al.,*2025). In PM, more attention is paid to fairness and privacy issues, thus easily raising doubts and concerns (Biswas *et al.,* 2024; Majrashi,2025).

The t-test results showed that the difference in the means of the two variables was -0.146, t=-1.845, p=0.068. It did not reach the statistical significance standard. However, Cohen's d=0.747, which is a moderately large effect size, suggests that the difference may have some significance in practice. Specifically, although the current sample does not support a significant difference, the data indicates that employees' acceptance of TD is trending higher. Future research can further verify this finding by increasing the sample size or using more precise measurement methods.

Table 7. Paired-Samples T-Test Results for employees’ Attitudes Towards AI in PM and TD

Comparison variables	Positive_PM	Positive_TD
Mean	3.78	3.92
SD	0.914	0.869
Correlations	0.65	
P-value (Correlation)	<.001	
Mean Differences	-0.146	
Std. Error Differences	0.079	
T-value	-1.845	
P-value (t-test)	0.068	
Degrees of Freedom(df)	88	
Cohen's d (Effect Sizes)	0.747	

Note. SD= Std. Deviation

Considering that attitudes towards these two application scenarios may vary among different age groups. Therefore, the study introduced the age variable for a two-factor repeated measures analysis of variance. Descriptive statistics show (see Table 8) that, overall, employees' acceptance of TD (M=3.92) is higher than that of PM (M=3.78). The results of analysis of variance (Table 9) indicated that the scene main effect was not significant (F-statistic=0.044, p= 0.835), while the age main effect was close to the significant level (F-statistic = 2.644, p=0.054), suggesting that there might be differences in acceptance among group members of different ages.

It is worth noting that there is a significant interaction between age and scenarios (F-statistic=2.860, p= 0.042), indicating that the preference patterns of different age groups in the two scenarios will change with age. Specifically, the 18-49 age group generally held a higher score for TD. The differences are more obvious in the 40-49 age group. However, 50 and the previous group showed the opposite trend, with a greater preference for PM (M=5). It should be emphasized that the sample size of this group was extremely small (n=2), and the results were not representative. This discovery suggests that employees' preferences for AI application scenarios may vary with age. Future research can expand the sample size of the older age group to further explore these psychological and situational factors.

Table 8. Means and Standard Deviations of AI Acceptance in PM and TD across Age Groups

Age	n	Mean	PM-SD	Mean	TD- SD
18-29	44	3.98	0.902	4.11	0.754
30-39	35	3.54	0.852	3.66	0.968
40-49	8	3.38	0.916	4	0.767
50 or above	2	5	0	4	1.414
Total	89	3.78	0.914	3.92	0.869

Note. SD=Std. Deviation

Table 9. Repeated Measures ANOVA Results for Age, Scenario, and Their Interaction on AI Acceptance

<table>
<tr><th colspan="2">Effect</th><th>Type III Sum of Squares</th><th>df</th><th>Mean Square</th><th>F</th><th>P</th><th>partial η^2</th></tr>
<tr><td rowspan="3">Within-Subjects Effects</td><td>Scenario(age)</td><td>0.011</td><td>1</td><td>0.011</td><td>0.044</td><td>0.835</td><td>0.001</td></tr>
<tr><td>Scenario (age * Q1)</td><td>2.251</td><td>3</td><td>0.75</td><td>2.86</td><td>0.042</td><td>0.092</td></tr>
<tr><td>Error(age)</td><td>22.3</td><td>85</td><td>0.262</td><td></td><td></td><td></td></tr>
<tr><td rowspan="2">Between-Subjects Effects</td><td>Age(Q1)</td><td>9.849</td><td>3</td><td>3.283</td><td>2.644</td><td>0.054</td><td>0.085</td></tr>
<tr><td>Error</td><td>105.556</td><td>85</td><td>1.242</td><td></td><td></td><td></td></tr>
</table>

Note. F =F-statistic， partial η^2= Partial Eta Squared， P= Sig.

Question 3, In the two application scenarios of PM and TD, among the three factors of privacy concerns, perceptions of fairness, and lack of interpersonal interaction, which one is most significant?

Performance management

The results of descriptive and correlation analysis (Table 10) show that the average acceptance of AI in PM scenarios among 89 employees is 3.78 (SD=0.914). And all independent variables were significantly positively correlated with acceptance (Sig. (1-tailed) <0.05). Among them, the correlation between PM efficiency and acceptance was the highest (r =0.477, P<0.001). It conforms to the view in the literature that AI can significantly enhance HR efficiency and decision-making quality (Kshetri, 2021; Bhushan, 2023; Benabou and Touhami, 2025; Gong *et al.,*2025). Regression analysis (Table 11) indicated that the overall statistics of the model were significant (df (8,80, f=6.882, P<0.001), Adjusted R Square =0.348. Table 12 shows that the tolerance value ranges from 0.712 to 0.858, the variance inflation factor (VIF) is less than 1.5, and the model is robust without severe collinearity.

Among the three core factors, privacy concerns (data collection, Unstandardized B(B)=0.036, Standardized Coefficients (Beta)= 0.031, P=0.745; Data leakage, B=0.092, Beta=0.088, P=0.367) and fairness perception (assessing fairness, B=0.092, Beta=0.088, P=0.367; The assessment transparency (B=0.169, Beta=0.162, P=0.151) had no significant impact on employee acceptance. It indicates that the independent predictive power for the willingness to accept is limited. This is consistent with the view in the literature that privacy and data security issues affect the willingness to accept AI (Sachan *et al.,*2024). On the contrary, the lack of interpersonal communication has a significant positive prediction for acceptance (B=0.230, Beta=0.218, t=2.257, P=0.027). It is suggested that some employees in PM prefer the efficient and non-emotional feedback provided by AI. This is in line with the common view in the literature that the lack of interpersonal interaction is a negative challenge for AI in HRM (Bankins *et al.,* 2022; Majrashi,2025) shows significant differences and provides a brand-new perspective for existing research

It is worth noting that the most significant is the performance expectation (B=0.429, Beta=0.363, t=3.782, P=0.001). The perception of efficiency is an important factor in acceptance, even surpassing the privacy concerns and perception of fairness that were the key focuses on the research. This is in line with the view in the literature that emphasizes employees' recognition of the efficiency value of AI (Duggan *et al.,* 2020; Norlander *et al.,* 2021 Dutta *et al.,* 2023).

Table 10. Descriptive Statistics and Correlation Analysis Results of Employees' Acceptance of AI in Performance Management (N=89)

	Mean	SD	r	P
Data Collection (CPM)	3.92	0.772	0.137	0.03
Data Leakage (CPM)	3.78	0.876	0.029	0.026
Evaluation Fair (POJ)	3.36	0.908	0.203	<.001
Evaluation transparency (POJ)	3.53	0.88	0.255	<.001
Communication (II)	3.61	1.04	0.086	0.045
Interaction (II)	4.1	0.867	0.136	<.001
Efficiency (PE)	3.89	0.775	0.477	<.001
Company support (SI)	3.67	0.836	0.399	0.003
Positive_PM	3.78	0.914		

Note. SD=St. Deviation; r= Pearson Correlation Coefficient; P =Sig. (1-tailed); POJ= Perceived Organization Justice; CPM= Communication Privacy Management Theory; II= Interpersonal Interaction; SI= Social Influence; PE=Performance Expectancy.

Table 11. ANOVA Results of the Regression Model

Model Summary	value
Adjusted R Square	0.348
F	6.882
df	8,80
P	<0.0001

Note. P=Sig.

Table 12. Collinearity

	B	Beta	t	P	Collinearity Tolerance	VIF
(Constant)	-0.515		-0.792	0.431		
Data Collection (CPM)	0.036	0.031	0.326	0.745	0.843	1.187
Data Leakage (CPM)	0.092	0.088	0.908	0.367	0.793	1.262
Evaluation Fairness (POJ)	0.165	0.164	1.454	0.15	0.583	1.716
Evaluation transparency (POJ)	0.169	0.162	1.45	0.151	0.59	1.694
Communication (II)	0.006	0.007	0.075	0.941	0.858	1.165
Interaction (II)	0.23	0.218	2.257	0.027	0.792	1.262
Efficiency (PE)	0.429	0.363	3.782	<.001	0.802	1.247
Company support (SI)	0.006	0.005	0.053	0.958	0.712	1.404

Note. B= Unstandardized B; Beta= Standardized Coefficients; P=Sig; POJ= Perceived Organization Justice; CPM= Communication Privacy Management Theory; II= Interpersonal Interaction; SI= Social Influence; PE=Performance Expectancy.

Training development

Descriptive statistics and correlation analysis (Table 13) show that the average acceptance of AI by employees in TD is 3.92 (SD=0.869), but not all independent variables are significantly correlated. The correlation between transparent recommendation and acceptance was the highest ($r=0.341$, $p<0.001$), followed by data leakage ($r=0.292$, $p=0.003$).

However, fair recommendation (r=0.072, P=0.250) and data collection (r=0.174, p=0.052) were not significant. This is consistent with the view in the literature that employees have a positive and open attitude towards AI in TD (Kong, 2024; Kochling *et al.,*2025).

Regression analysis (Figure 14) shows that the model has statistical significance in the TD scenario (df (8,80), f=6.020, P<0.001), which can explain approximately 31.3% of the employee acceptance variation, slightly lower than that in the PM scenario. The collinearity diagnosis (Figure 15) shows that the tolerance is between 0.555 and 0.755, and the VIF is between 1.324 and 1.82, indicating that there is no severe collinearity and the regression coefficient is reliable.

The coefficient analysis of multiple linear regression (Figure 15) shows that among privacy concerns, data leakage (P<0.05, B=0.226, Beta=0.209, t=1.764, P=0.082) and data collection (B=-0.118, Beta=-0.108, P=0.370) are not significant. It indicates that employees' concerns about data leakage in the TD scenario have a limited impact on acceptance. In fairness perception, transparent recommendation significantly positively predicted acceptance (B=0.342, Beta=0.365, t=3.587, P<0.001). It indicates that employees are more likely to accept AI when they perceive the recommendation mechanism as transparent and understandable. This discovery is consistent with the view of Kochling et al. (2025) that employees generally recognize the practicality of AI in TD, while emphasizing more attention to the source of data and the transparency of the program. However, fair recommendation was not significant (B=-0.093, Beta=-0.107, P=0.302). The lack of a learning atmosphere (B=-0.151, Beta=-0.159, P=0.144) and the lack of interaction (B=-0.056, Beta=-0.057, P=0.584) in human-computer interaction have no significant predictive power for acceptance. This indicates that in the TD scenario, employees' concerns that AI might reduce interpersonal interaction or lead to a lack of learning atmosphere have little impact.

It is worth noting that in the dimension of social impact, company support has the strongest predictive power of employee acceptance (B=0.439, Beta=0.434, t=4.209, P<0.001). It indicates that the company's clear support for AI is a key driver of acceptance. This is consistent with the core viewpoint of the social impact dimension in the model of UTAUT (Venkatesh *et al.,*2003) Furthermore, the impact of performance expectations in the TD scenario was not significant B (=-0.056, Beta=-0.047, P=0.652), in contrast to the significant effect in the PM scenario. It indicates that employees' focus on AI systems varies in different scenarios, which may affect the formation mechanism of their willingness to accept.

Table 13. Descriptive Statistics and Correlation Analysis Results of Employees' Acceptance of AI in Training and Development (N=89)

	Mean	SD	r	P
Data Collection (CPM)	3.79	0.79	0.174	0.052
Data Leakage (CPM)	3.85	0.806	0.292	0.003
Fair Recommendations (POJ)	3.51	1.001	0.072	0.25
Transparency Recommendations (POJ)	3.6	0.926	0.341	0.001
Interaction (II)	3.91	0.887	0.197	0.032
Learning Atmosphere (II)	3.91	0.913	0.177	0.048
Efficiency (PE)	3.8	0.726	0.191	0.037
Company support (SI)	3.74	0.86	0.429	0
Positive_TD	3.92	0.869		

Note. SD=St. Deviation; r= Pearson Correlation Coefficient; P =Sig. (1-tailed); POJ= Perceived Organization Justice; CPM= Communication Privacy Management Theory; II= Interpersonal Interaction; SI= Social Influence; PE=Performance Expectancy.

Table 14. ANOVA Results of the Regression Model

Model Summary	value
Adjusted R Square	0.313
F	6.020
df	8,80
P	<0.0001

Note. P=Sig.

The coefficient analysis results of multiple linear regression in Table 15 reveal the independent predictions of each factor on acceptance:

Table 15. Collinearity

	B	Beta	t	P	Collinearity Tolerance	VIF
(Constant)	0.356		0.513	0.609		
Data Collection (CPM)	-0.118	-0.108	-0.902	0.370	0.549	1.82
Data Leakage (CPM)	0.226	0.209	1.764	0.082	0.555	1.801
Fair Recommendations (POJ)	-0.093	-0.107	-1.039	0.302	0.729	1.371
Transparency Recommendations (POJ)	0.342	0.365	3.587	<0.001	0.755	1.324
Interaction (II)	0.056	0.057	0.549	0.584	0.728	1.373
Learning Atmosphere (II)	0.151	0.159	1.476	0.144	0.672	1.488
Efficiency (PE)	-0.056	-0.047	0.453	0.652	0.737	1.357
Company support (SI)	0.439	0.434	4.209	<0.001	0.733	1.365

Note. B= Unstandardized B; Beta= Standardized Coefficients; P=Sig; POJ= Perceived Organization Justice; CPM= Communication Privacy Management Theory; II= Interpersonal Interaction; SI= Social Influence; PE=Performance Expectancy.

4.5 Summary

This chapter presents the acceptance of AI by employees in the PM and TD HR scenarios and the influencing factors. Overall, employees hold an open attitude towards AI in HRM and show a relatively positive view. Although the TD scenario is slightly higher than the PM scenario, the difference is limited. Preliminary analysis also suggests that there may be an interaction between the age of employees and the scenarios, and different age groups have differences in their acceptance patterns of AI. Due to the small sample size in some age groups, further verification needs to be achieved by expanding the sample size in subsequent studies.

In PM, efficiency perception is a key factor driving employees to embrace AI, and some employees even accept the reduction in interpersonal communication. This discovery challenges the existing literature view that the lack of interpersonal interaction is the main obstacle to the adoption of AI. This indicates that in a context emphasizing efficiency, employees may place greater emphasis on process optimization and rational feedback. However, the impact of privacy concerns and fairness perception is relatively limited. In TD, employees' willingness to accept is mainly driven by the company's support and the transparency of recommendations. It reflects the importance of organizational attitude and system trust in learning-oriented contexts. However, the impact of performance expectations, privacy and perception of fairness is relatively limited.

Overall, employees' acceptance of AI is influenced by the combined effects of scene characteristics, organizational atmosphere and personal perception. In PM, efficiency is the focus; in TD, trust and support are even more crucial. Therefore, when organizations implement AI technology, they should pay attention to the synergy of multiple factors to promote a positive interaction between technological effectiveness and employee acceptance. Just as the research in the literature review pointed out, employees' attitudes towards AI technology will affect their adoption and usage effects. Similarly, the implementation effect of AI will also shape employees' views, and there is a continuous feedback and interaction mechanism between the two (Taslim *et al.,*2025).

Chapter five——Discussion and Conclusion

5.1 Introduction

This chapter based on research findings, conducts an in-depth analysis of the acceptance of artificial intelligence (AI) in the fields of performance management (PM) and training and development (TD). By analysing the key factors influencing employees' acceptance, this paper attempts to reveal the psychological and behavioural mechanisms behind them and compares the findings with existing literature to provide theoretical and practical insights.

5.2 Main findings

Firstly, employees hold a positive and open attitude towards the application of AI in HRM, which is consistent with the results of Shah's (2023) study that most employees tend to use AI in HRM.

Secondly, acceptance varies across different application scenarios. Although it does not reach a significant level, TD is slightly higher than PM, reflecting the differences in employees' perception of risks and value judgments. This is consistent with the results of existing studies that generally hold a positive attitude towards the role of AI in TD (Kong, 2024; Kochling *et al.,*2025; Reina-Parrado, Roman-Gravan and Hervas-Gomez,2025), while PM focuses more on ethical challenges such as fairness and privacy risks (Park,2021; Varma *et al.,* 2024; Majrashi,2025).

In addition, further analysis revealed the differences in key factors influencing employees' acceptance in various scenarios.

Efficiency perception in PM is the strongest factor influencing employee acceptance, which is consistent with the view in the literature that employees recognize AI for improving efficiency (Dima *et al.,*2024). Furthermore, the lack of interpersonal communication also has a positive impact on acceptance. This discovery forms an interesting contrast with the traditional view and may reflect that employees expect to enhance efficiency and reduce the negative impact of interpersonal conflicts through AI feedback. This is in line with the view in the literature that evaluation methods based on fixed rules or algorithms are regarded as more objective and neutral and thus are more easily accepted by employees (Biswas, Talukder and Khan,2024).

Corporate support is the strongest factor influencing acceptance in TD, which is consistent with the emphasis in existing literature on the key role of organizational environment and leadership in technology adoption (Kong,2024; Reina-Parrado, Roman-Gravan and Hervas-Gomez,2025). Meanwhile, transparent recommendation also has a significant positive impact on acceptance. This finding is consistent with the expectations of employees in the literature regarding the transparency and interpretability of the recommendation mechanism of AI (Kochling *et al.*,2025).

5.3 Explanation

Discovery 1

Research data shows that employees' attitudes towards AI in HRM are generally positive and open, which directly responds to the first research question of this study. The average overall acceptance of AI applications by the samples was 3.77, with both the median and mode being 4. It indicates that most respondents tend to "agree" or "strongly agree" with the relevant statements. This result is consistent with the research conclusion of Bhatt and Shah (2023) that employees generally show a high acceptance of AI.

Explain from the perspective of the Technology Acceptance Model (TAM). Although this study did not model and analyse "perceived usefulness" and "perceived ease of use" separately, the high scores given by employees in the relevant items indicate their recognition of the potential of AI in improving efficiency and simplifying processes in HRM. This tendency is in line with the theory of the TAM model, that is, an individual's technology adoption behaviour is mainly influenced by two major factors: perceived usefulness and perceived ease of use. Therefore, it can be initially concluded that the adoption of technology mainly affects perceived usefulness and ease of use, indicating that employees' openness to AI may stem from their recognition of its functional value.

Discovery 2

Although it did not reach a significant level statistically, employees' acceptance of TD was slightly higher than that of PM. This directly responds to research question two. A literature review shows the differences in the roles played by AI in various HR scenarios and its impact on employee interests.

AI is often used in TD for personalized learning, skills and ability enhancement (Kong, 2024; Kochling *et al.*,2025; Reina-Parrado, Roman-Gravan and Hervas-Gomez,2025), is regarded as a supportive and non-critical tool with low risk and functions that directly enhance learning efficiency and career growth. Therefore, it is perceived as highly useful and more easily accepted by employees.

In contrast, PMS are directly related to core interests such as employee compensation, promotion, and career development, with high stakes. Employees are more concerned about assessment fairness and data privacy (Park,2021; Varma *et al.*, 2024; Biswas *et al.*, 2024 Majrashi,2025; Majrashi,2025), thereby possibly reducing perceived usefulness and having a relatively lower acceptance of AI.

Therefore, from the perspective of the TAM model, the perceived usefulness of AI is more prominent in TD, while in PM, concerns over fairness and privacy weaken this perception, which explains the difference in acceptance.

Discovery 3

Further analysis shows that the key factors influencing employees' acceptance vary depending on the application scenario. This directly responds to research question three.

Efficiency perception is the strongest predictor variable in PM. It indicates that employees are concerned about whether AI can enhance assessment efficiency, provide timely feedback and reduce human errors. This is consistent with the dimension of performance expectation in the UTAUT theory (Venkatesh *et al.*,2003), that is, an individual's expectation of the improvement of technical performance is a key factor influencing adoption behaviour.

Furthermore, the lack of interpersonal communication has a positive impact on acceptance. This traditional view emphasizes that supervisors provide emotional support and personalized guidance in performance feedback, creating a contrast (Biswas *et al.,* 2024). The possible reason is that PMS are directly related to the key interests of employees. Under such a background, the evaluation of AI based on fixed rules or algorithms is regarded as more objective and neutral, thereby obtaining a higher level of trust (Biswas *et al.,* 2024). It explains the significance of efficiency and fairness in this scenario.

In TD, corporate support is the strongest predictor variable, which is consistent with the social influence dimension in UTAUT theory, that is, individuals are influenced by others' expectations of their use of a certain technology, and its effect is more significant in the mandatory use scenario and the early use stage (Venkatesh *et al.,*2003) It indicates that employees' positive perception of AI not only depends on the practicality of the technology, but is also influenced by the importance of organizational support and interpersonal interaction. Existing research also indicates that employees' positive perception of AI is significantly positively correlated with support resilience and informal learning behaviours (Kong,2024; Reina-Parrado, Roman-Gravan and Hervas-Gomez,2025). Furthermore, the demands of employees for AI systems in terms of emotional support, interactive feedback and social connection further highlight the key role of social influence in promoting the acceptance of AI applications (Wanner *et al.,*2018).

Meanwhile, transparent recommendation has a significant positive impact on acceptance, which can be explained by the Communication Privacy Management Theory (CPM), that is, when individuals share and receive information, they attach importance to the transparency and control of information (Petronio and Child,2002). Meanwhile, when the decision-making logic and training recommendation mechanism of the AI system are clear and understandable, employees' trust and willingness to adopt will be significantly enhanced (Kochling *et al.,*2025). This shows that transparency not only enhances understandability but also alleviates the perception of privacy risks and promotes employees' willingness to adopt.

5.4 Theoretical implications

The findings of this study provide new insights for the TAM theory, emphasizing the contextualized differences in technology acceptance behaviour across various application scenarios. Although the technology acceptance was not subdivided into perceived usefulness and perceived ease of use for measurement, it was observed that the differences in acceptance provided clues for understanding the driving mechanisms behind them. Therefore, future research can further consider the connection between the application scenarios of technology and the core interests of employees, taking specific scenarios as moderating variables to more accurately predict the adoption behaviour of employees.

Meanwhile, this study also provides a new perspective for the UTAUT model. Research has found that non-technical variables also play a key role in explaining employees' acceptance of AI. The importance of social psychological factors such as fairness perception, privacy concerns, and interpersonal interaction is comparable to that of the core variables of UTAUT. Therefore, in the future, these non-technical variables can be considered to promote the scenario expansion of the UTAUT model and better reflect the true attitudes and behaviours of employees in complex organizational environments.

5.5 Practical implications

The findings of this study provide important inspirations for enterprises in the practical application of AI. The results show that employees' attitudes towards AI in HRM are generally positive and open, but the acceptance degree varies depending on the application scenarios and is affected by different key factors. Therefore, in practice, enterprises should avoid a single promotion model and adopt a differentiated strategy, considering both employees' perception of the value of AI and their risk assessment.

In PM, the advantages of AI in enhancing efficiency and evaluating objectivity should be highlighted. At the same time, in response to employees' concerns about fairness and privacy, the transparency and explainability of the system should be improved, and a sound data security guarantee mechanism should be established. In TD, the promotion focus should be placed on creating a supportive environment, strengthening organizational support, providing sufficient training and resources, and emphasizing the role of technological transparency in building employee trust, thereby promoting the formation of a culture of AI adoption and active application.

5.6 Future research directions

This study initially observed that there may be differences in employees' acceptance of AI in PM and TD at different age stages. This trend suggests that individual characteristics, especially generational differences, may be important factors influencing the acceptance of AI, providing a new direction for future research. Although this study did not delve deeply into this variable, the related phenomenon is worthy of systematic verification in future research. Subsequent research can further examine how demographic variables such as age, occupational stage, and technical familiarity affect employees' acceptance attitudes towards AI, and explore whether there are differentiated psychological mechanisms in different HRM application scenarios, thereby enriching the individualized interpretation framework of the technology acceptance model and providing theoretical support for more targeted AI promotion strategies.

5.7 Conclusion

This study aims to explore the differences in employees' acceptance of AI in different HRM application scenarios and its influencing factors. The results show that employees hold a positive and open attitude towards the application of AI in HRM, but there are differences in acceptance in different TD and PM scenarios, reflecting the differences in employees' perceived value and perceived risk of AI in different situations. Further analysis indicates that in PM, efficiency perception is the strongest factor, and the lack of interpersonal communication has a positive impact, emphasizing the importance of AI objectivity and efficiency. In TD, the company's support and transparent recommendations are key factors, reflecting the role of organizational atmosphere and technical explainability in building trust.

At the theoretical level, this study provides a contextualized supplement to the application of TAM and UTAUT models in AI-driven HRM contexts. The research reveals that employees are not only influenced by technical factors but also by social psychological factors such as perception of fairness, privacy concerns, and interpersonal interaction. These findings not only expand the existing theoretical models but also provide empirical evidence for future related research in HRM.

This study provides a contextualized extension for the application of TAM and UTAUT models in AI-driven HRM contexts, revealing the impact of psychosocial factors such as fairness perception, privacy concerns, and interpersonal interaction on employee acceptance. In practice, enterprises should adopt differentiated strategies when promoting the application of AI. In PM, emphasize efficiency and objectivity, and reduce subjective assessment. Strengthen the transparency of organizational support and recommendations in TD to enhance trust and willingness to adopt. Despite the limited sample size, the study still revealed situational differences in AI acceptance, providing a reference for future expansion of the sample size and in-depth exploration of the impact of individual characteristics.

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