International Journal of Public Policy and Administration Research
2025 Vol. 12, No. 2, pp. 151-167
ISSN(e): 2312-6515
ISSN(p): 2313-0423
DOI: 10.18488/74.v12i2.4269

Assessing the key drivers of acceptance of AI-based employee management across varied levels of employees working in the Australian IT industry

Xinyang Zhang[1]
Sanghyuk Yim[2+]

[1,2]*Dankook University, Yongin-si, Korea.*
[1]*Email: zhangxinyang0728@163.com*
[2]*Email: shyim310@dankook.ac.kr*

(+ Corresponding author)

Article History
Received: 10 January 2025
Revised: 13 June 2025
Accepted: 25 June 2025
Published: 2 July 2025

Keywords
AI-based employee management
Artificial intelligence
Employee levels
Privacy and security
Training and development
Transparency and fairness.

ABSTRACT

The purpose of this study is to assess key drivers of acceptance of AI-based employee management across various levels of employees working in the Australian IT industry. In the Australian IT industry, AI adoption in HRM, specifically in employee management, is increasing rapidly. Quantitative data collection and analysis have been conducted for this research. Data was collected from social media groups. Although the initial pool of candidates was 456, a total of 257 responses were received. After filtering out incomplete and invalid responses, 216 responses were considered for analysis. The results showed that the most significant driver of acceptance of AI-based employee management in the Australian IT industry, which ensures corporate social responsibility, is perceived transparency, fairness, and training and development sessions to enhance AI-related knowledge. There is no significant relationship between privacy and security and employee acceptance of AI integration into the employee management system. The positional level of employees in the Australian IT sector itself is a driver of higher AI acceptance. It has been suggested that managers prioritize CSR-driven initiatives, such as enhancing perceived transparency and fairness through the implementation of ethical AI practices. Additionally, both higher-level and lower-level employees should be involved in AI implementation processes to increase their acceptance levels.

Contribution/Originality: This research extends current literature by establishing principal drivers for AI-based management of employees in Australia's IT industry, combining CSR and employee designation in a distinctive manner. Unlike previous research conducted solely on AI and HRM, it presents a new, ethical, and pragmatic approach to facilitate successful AI implementation.

1. INTRODUCTION

The rapid adaptation of Artificial Intelligence (AI) in business has transformed work procedures. The integration of AI in Human Resource Management (HRM) has changed how organizations handle recruitment, performance evaluation, talent management, and employee management (EM). AI-driven tools are used to streamline recruitment, conduct data-driven performance reviews, and support effective decision-making (Yanamala, 2020). However, Makarius, Mukherjee, Fox, and Fox (2020) stated that the integration of AI also raises a wide range of challenges that affect its acceptance among different levels of employees. Therefore, despite the potential of AI to ensure better organizational and employee performance and productivity, employee acceptance varies based on a wide range of concerns such as privacy, transparency, fairness, and accountability. Employees at different levels often feel that AI-driven performance valuation is biased because it cannot consider individual circumstances (Yanamala, 2020). These concerns can increase job insecurity and a lack of loyalty towards the organization, leading to deteriorating employee and organizational performance. However, Gao and Segumpan (2024) argued that a significant number of employees had shown a higher preference for AI-driven performance evaluation since they perceive AI demonstrates higher fairness and objectivity compared to manual performance evaluations. Chukwuka and Dibie (2024) noted that most employees respond positively to the timely and objective nature of AI-driven performance evaluations, which significantly increases their acceptance rate. Therefore, there are varied opinions regarding the acceptance of AI-based employee management across different levels.

When it comes to the Australian IT industry, the AI adaptation in HRM, specifically in EM, is increasing at a rapid pace (Yang, Blount, & Amrollahi, 2024). Specifically, high client expectations, along with competitive pressure, have accelerated AI adoption in the IT industry. This means that the goal of this rapid AI adoption in EM is to retain skilled employees and ensure higher performance and productivity, so that pressure can be managed and a competitive advantage can be gained. Additionally, technological readiness and management support are key drivers of this rapid adoption. Furthermore, increased access to innovation hubs and a higher percentage of employees with technological knowledge are helping the HRM departments of Australian IT organizations to implement AI integration (Prikshat et al., 2023). This has made it highly crucial to understand the key factors that are driving employees of different levels' acceptance of AI-driven employment management. Gandía, Gavrila, de Lucas Ancillo, and del Val Núñez (2025) have highlighted ethical decision-making by AI plays a crucial role in ensuring its acceptance among employees. Therefore, organizations that use AI-based EM systems as part of Corporate Social Responsibility (CSR) to ensure employee well-being and ethical practices, along with enhancing their performance and productivity, are more likely to have higher acceptance of AI-driven EM systems. However, a limited amount of literature has been found regarding the degree of acceptance of IT employees towards AI-driven EM and CSR.

While evaluating existing literature, it has been found that, currently, the specific effect size of each key ethical driver on AI acceptance factors in HRM has not been explored. Some of the major weaknesses in previous literature include a lack of quantifiable effects of each driver of AI acceptance. Addressing this weakness, this paper uniquely identifies the effect of each key ethical driver on the acceptance of AI. The conflict of interest regarding AI integration among different employee levels has already been well explored. This paper uniquely identifies the moderating role of various levels of employees, considering the effect sizes of each level or job position. IT in Australia is growing with the increasing trend of AI integration. This paper can provide beneficial managerial guidance for the future of the Australian IT industry. Furthermore, fewer existing studies have analyzed the adoption of AI in HRM from the perspective of CSR, specifically in the Australian IT sector. This paper analyzes the relationship between CSR and AI in employee management.

2. LITERATURE REVIEW

2.1. Artificial Intelligence

Kok, Boers, Kosters, Van der Putten, and Poel (2009) and Wang (2019) have defined AI as a set of technologies that can simulate or mimic human intelligence enabling tasks like problem-solving, reasoning, and perception. AI in EM can be defined as the application of AI-driven tools to analyze employee management practices like analyzing employee performance, automating routine tasks, and increasing employee engagement and satisfaction (Ganatra & Pandya, 2023). Abhari, Bhullar, Le, and Sufi (2023) stated AI is integrated into employer management since it can improve the experience of the employees through predictive analytics and personalized feedback. However, Budhwar, Malik, De Silva, and Thevisuthan (2022) claim that despite the advantage offered by AI and other automation intelligence technologies in optimized benefits, organizations often fail to ensure transparency. For instance, organizations make decisions about employees based on outputs provided by AI-based systems, which are not primarily transparent to employees. Eventually, if employees fail to understand how decisions are made or refrain from accepting decisions made using AI-based systems, it can result in adversarial employee behaviors.

2.2. Employee Management

As per Decramer, Smolders, and Vanderstraeten (2013), EM is the structured approach to developing, managing, and motivating employees so that their performance can be aligned with the organizational goals. Moreover, Heinfeldt and Curcio (1997) claimed that EM is a crucial part of HRM that includes processes like performance appraisal, training, and engagement strategies that can build a motivated and productive workforce. Therefore, effective EM is critical for ensuring a collaborative and effective organizational culture that can contribute to both individual and business growth.

2.3. Corporate Social Responsibility

CSR represents the commitment of an organization to contribute to society by implementing ethical practices so that sustainable development can be ensured (Moon, 2007). Masum, Aziz, and Hassan (2020) highlighted CSR activities not only include improving the welfare of communities and the environment beyond profit making but also include ensuring the welfare of the employees. Therefore, ensuring ethical EM through AI-driven data, which can improve employees' skills along with their well-being, can be considered a major part of organizational CSR. Hansen, McDonald, and Hatfield (2023) highlighted that while a significant number of organizations consider CSR activities as a responsibility to be fulfilled spontaneously to ensure sustainable business practices, several companies opt for CSR to gain goodwill from consumers and a competitive advantage. Overall, CSR has become a crucial part of corporate strategy, aligning business objectives with social and environmental goals while fostering a positive organizational image.

2.4. Transparency and fairness as Drivers of Acceptance of AI-based Employee Management

Transparency and fairness are key drivers of the acceptance of AI-based EM systems among employees. Higher adherence to AI ethical standards and a greater degree of transparency in AI operations are two major factors influencing employee acceptance of AI-driven EM systems (Schmidt, Biessmann, & Teubner, 2020). A significant number of employees perceive that, unlike manual appraisal systems, AI-based appraisal systems are more transparent. Chukwuka and Dibie (2024) agreed and added that AI-based appraisal systems offer transparency by consistently applying data-driven models across evaluations, which employees see as more objective and fairer than traditional, manually administered evaluations. However, Hetterich (2020) argued that algorithmic biases arising from biased training data or incorrect algorithm design could discriminate in HR decision-making, disadvantage demographic groups, or perpetuate structural injustices. Consequently, the fear of fairness loss during performance evaluation can reduce employees' acceptance of an AI-driven EM system. When these systems operate with little insight into how users have reached their conclusions, employees tend to distrust the algorithms' intentions and question their accuracy (Connelly, Fieseler, Černe, Giessner, & Wong, 2021). Furthermore, Arslan, Cooper, Khan, Golgeci, and Ali (2022) claim that a significant number of HR managers lack critical skills and training in modern technology-enabled tools such as AI-driven EM systems. This deficiency can potentially have adverse consequences for employees and organizations, hindering fairness and transparency in performance evaluation and employee management. Such issues may lead to mistrust and impede the acceptance of AI in workplace management, as concerns about fairness and the basis for automated decisions persist among employees. Therefore, while some employees believe that AI-driven EM systems ensure higher adherence to ethical standards and greater transparency, a notable portion of employees believe that AI integration in management systems increases the risks of algorithmic bias, resulting in greater opacity in decision-making (Mensah, 2023). Based on the findings of this literature, the following hypothesis has been developed.

H_1: Perceived transparency and fairness have a significant effect on the acceptance of AI-based employee management systems among employees working in the Australian IT industry.

2.5. Training and Development as a Driver of Acceptance of AI-Based Employee Management

Training and development are key drivers of employee acceptance of AI-driven EM systems. Rane, Choudhary, and Rane (2024) stated that the provision of training sessions for effectively using AI systems to increase the acceptance of AI minimizes the fear related to job security and thereby prepares employees for AI-driven employees' management. Therefore, effective training and development sessions for employees are essential to help them understand the AI-driven EM system and enhance their acceptance of it. Nyathani (2023) agreed with Rane et al. (2024), highlighting that employees show more confidence in AI-driven EM systems when they are provided with effective knowledge and training sessions that help them understand how AI contributes to performance management. Furthermore, Brougham and Haar (2020) have opined that relevant and meaningful training is critical for reducing employees' negative feelings towards new technological adaptations like AI-based systems, as training enables employees to learn and understand how to use these AI systems. Thus, creating a new culture and organizational redesign can help overcome technological obstacles in the workplace.

H_2: Training and development have a significant effect on the acceptance of AI-based employee management systems among employees working in the Australian IT industry.

2.6. Employee Privacy and Security as a Driver of Acceptance of AI-based Employee Management

Karamthulla, Tadimarri, Tillu, and Muthusubramanian (2024) highlighted that a significant number of employees in data-sensitive industries such as IT show resistance towards AI-driven performance management, as higher integration of AI is associated with an increased risk of data piracy and other employee privacy and security concerns. Rane et al. (2024) added that many employees in the transport industry lack acceptance of AI-driven EM employee management because it compromises their privacy through round-the-clock tracking and monitoring of their electronic devices. The authors have emphasized that constant surveillance, which is part of many AI-driven employment management systems, creates a sense of intrusion into employees' personal lives, ultimately reducing their acceptance of these systems. According to a study by Behn, Leyer, and Iren (2024), the majority of employees cite privacy and security concerns as key reasons for rejecting employee analytics systems and software. Based on these findings, the following hypothesis has been developed.

H_3: Employee privacy and security have a significant effect on the acceptance of AI-based employee management systems among employees working in the Australian IT industry.

2.7. Employee Designation Level and Acceptance of AI-based Employee Management

Choi (2021) stated that higher-level employees have been found to have a better understanding of the merits and functionalities of AI-based EM, which automatically enhances their degree of acceptance of the same. Conversely, lower-level employees lack acceptance of AI-based EM systems, as they are more likely to face uncertainties in decision-making, which increases their resistance to AI-driven EM systems. Velanganni and Bhuvaneswari (2024) noted that higher-level employees, particularly managerial staff, are more likely to prefer and accept AI-driven employee management systems because these systems reduce their workload and simplify workforce management. Conversely, employees at lower levels may require additional training and reassurance regarding the implications of AI on their roles, which can influence their overall acceptance. Madan and Ashok (2023) highlighted that higher-level employees associate the use of AI-driven performance evaluations with transparency and fairness, while lower-level employees perceive AI-based target setting as rigid and impersonal. Unlike entry-level employees, AI-driven EM systems are less likely to threaten the roles of managers and higher officials since leadership roles require judgment and creativity beyond AI's capabilities. Hence, based on the findings of this literature, the following hypothesis has been developed.

H_4: Employee designation level moderates the relationship between transparency and fairness, as well as the employee management system.

H_5: Employee designation level has a moderating effect on the relationship between training and development and the employee management system.

H_6: Employee designation level moderates the relationship between employee privacy and security and the employee management system.

2.8. Theoretical Framework

2.8.1. Technology Acceptance Model

Technology adoption depends on perceived utility and ease of use, according to TAM. This theory emphasizes how the perceived usefulness of technology, along with its perceived ease of use and external factors such as transparency and fairness, influence employees' behavioral intention to adopt the AI system (Khair, Mahadasa, Tuli, & Ande, 2020). This theory aligns with the focus of this research to understand how factors such as transparency, fairness, training and development, and privacy and security are shaping the perceived usefulness and perceived ease of use of AI across different industry levels.

2.8.2. Resource Dependence Theory

The Resource Dependence Theory states that organizations require external resources, especially technology, to achieve success (Khair et al., 2020). AI technologies help HR decision-makers improve processes, reduce costs, and increase productivity. HR organizations can streamline talent management using AI for resume screening, candidate matching, and performance reviews.

2.8.3. The Theory of Innovative Diffusion

This theory explains the introduction of AI EM systems at different levels of employees in the Australian IT industry. It describes five characteristics that determine adoption: relative advantage, compatibility, complexity, trialability, and observability. These factors align with the socio-scientific perspective on transparency, fairness, and ethical aspects of AI benefits. The theory further explains different categories of adopters (e.g., innovators and laggards), which accounts for why some employees at higher levels accept more than those at lower levels. With this conceptual background, the research examines the processes of diffusion of AI technologies within organizational entities and their specific cultures.

2.9. Research Questions

1. What are the key drivers of acceptance of AI-based employee management in the Australian IT industry that ensure corporate social responsibility?
2. How does the level of employees (ground, lower, middle, and upper management) moderate the relationship between these drivers and the acceptance of AI-based employee management?

2.10. Hypothesis and Conceptual Framework

H_1: Transparency and fairness are major key drivers of acceptance of AI-based employee management systems among employees working in the Australian IT industry.

H_2: Training and development have a significant effect on the acceptance of AI-based employee management systems among employees working in the Australian IT industry.

H_3: Employee privacy and security are key drivers of acceptance of AI-based employee management systems among employees working in the Australian IT industry.

H_4: Employee designation level moderates the relationship between transparency and fairness, as well as the employee management system.

H_5: Employee designation level moderates the relationship between training and development and the employee management system.

H_6: Employee designation level moderates the relationship between employee privacy and security and the employee management system.

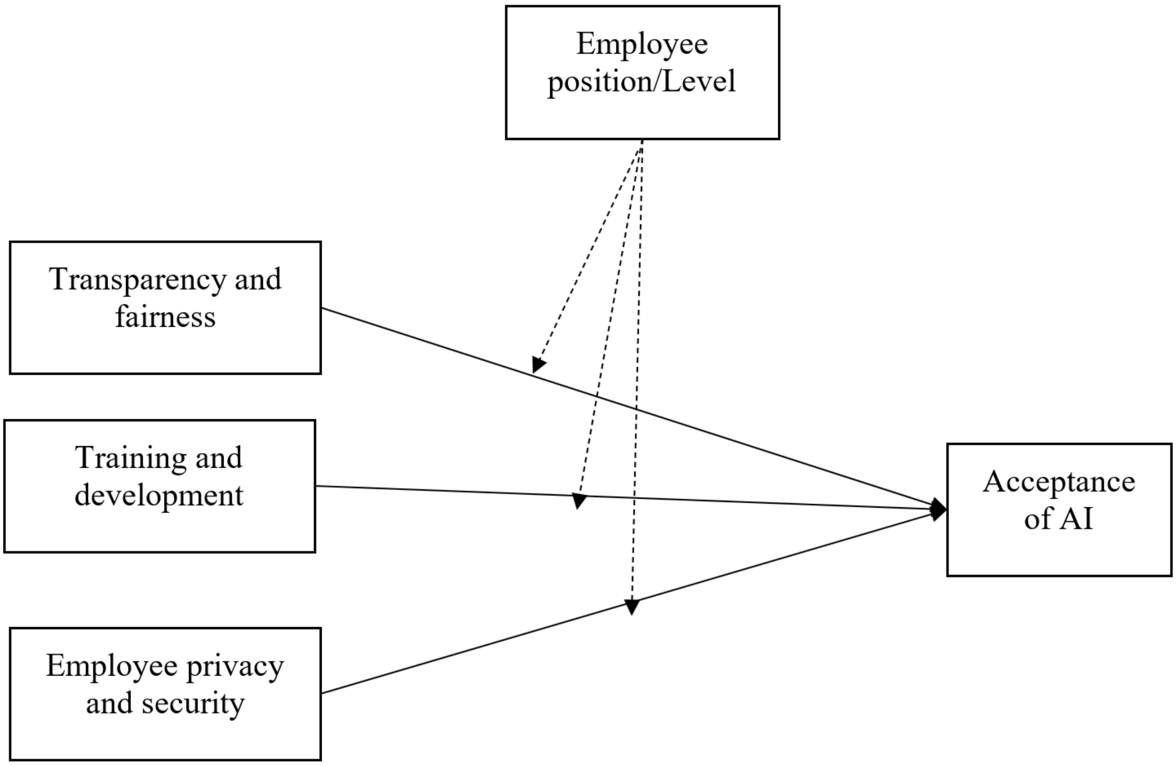

Figure 1. Conceptual framework.

Figure 1 illustrates the primary factors that influence the acceptance of AI in employee management. Transparency and fairness, training and development, and employee privacy and security directly affect AI acceptance. Employee position or level also moderates these relationships, indicating that attitudes towards these factors and their influence on AI acceptance vary depending on the employee's position or level within the organization.

3. METHODOLOGY

3.1. Target Population and Sampling

The targeted population for this research included ground, middle, and upper-level employees of the Australian Information Technology industry. Since the aim of this paper is to examine the key drivers of acceptance of AI-based EM across various levels of employees working in the Australian IT industry, the selected target audience comprises employees at all levels. Non-probability convenience sampling was used for this study. The primary reason for employing this sampling method was to ensure quick access to candidates who were readily available and willing to participate without ensuring representativeness. Although the total pool of candidates was 456, initially, 257 responses were received. After filtering out incomplete and invalid responses, 216 responses were considered for analysis.

3.1.1. Sample Characteristics

As per Table 1, 50% of the participants are male, and 39% are female, indicating that male participants are more prevalent in the targeted population. It has been found that the majority of participants are aged 20 to 49 years (80%), representing a young and middle-aged workforce. Furthermore, 71% of the participants have 1 to 10 years of experience in the IT industry, ensuring the authenticity and validity of their responses. Additionally, the sample reflects a realistic stratification of the IT industry workforce.

Table 1. Demographic and background characteristics of participants.

Demographic characters	Options	Count	N %
Gender	Male	108	50.00%
	Female	84	38.89%
	Other	6	2.78%
	Prefer not to say	18	8.33%
Age	20 to 29	45	20.83%
	30 to 39	78	36.11%
	40 to 49	51	23.61%
	50 to 59	30	13.89%
	60+	12	5.56%
Experience	Less than 1 year	9	4.17%
	1 to 5 years	45	20.83%
	6 to 10 years	108	50.00%
	11 to 20 years	30	13.89%
	More than 20 years	24	11.11%
Position level	Ground level	108	50.00%
	Lower-level manager	54	25.00%
	Middle-level manager	36	16.67%
	Upper-level manager	18	8.33%

3.2. Data Collection Process

Primary quantitative data collection has been performed for this study to ensure the data collected is first-hand, specifically answering the research question of this study. A quantitative method has been undertaken to measure phenomena involving the evaluation of AI acceptance factors such as fairness and transparency, training, security, and privacy, and to conduct statistical assessments using structured survey data. Online data will be collected through social media groups consisting of employees at all levels working in the Australian IT industry. First, the researcher sent requests to join two Facebook groups and two LinkedIn groups that included base-level, mid-level, and higher-level employees of Australian IT firms. The requests were accepted by two Facebook groups and one LinkedIn group admin. Then, a Google Form link containing a set of 20 questions was posted in the groups, along with a post explaining the research's purpose, followed by a request for participation in the survey. The Google Form link was active for two months to maximize responses from participants. The questionnaire was structured into two sections: demographic and factor-based. The instrument used was a close-ended questionnaire with 5-point Likert scale-based measurement dimensions. The scale items (refer to Table 1) have been developed by Schmidt et al. (2020), Hetterich (2020), Rane et al. (2024), Nyathani (2023), Karamthulla et al. (2024), and Khair et al. (2020).

3.3. Data Analysis Process

For analyzing the numerical data collected from the survey, statistical analysis has been conducted. Firstly, a descriptive analysis of all items related to specific variables was performed. Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis was carried out using SMART PLS software. Subsequently, the correlation of latent variables was used to determine their interrelationships. The variables and their underlying items were loaded, and their loadings were used for AVE, CR, and Cronbach's alpha analysis. The basic SEM PLS was employed to assess factor loadings, overall model fit, and R-squared values. This facilitated a comparative and correlational analysis of key variables, such as the relationship between transparency and AI acceptance. Finally, bootstrap sampling with 50,000 samples was used to test the final SEM PLS model, considering coefficients for both the sample mean and the original sample.

Table 2. Measurement scale.

Variable	Question range	Items	Inspired from
Transparency and fairness	Q 5 – Q8	Transparency recruitment (TF1)	(Hetterich, 2020; Schmidt et al., 2020)
		Transparency appraisal (TF2)	
		Fairness recruitment (TF3)	
		Fairness appraisal (TF4)	
Training and development	Q9 – Q12	AI awareness (TD1)	(Nyathani, 2023; Rane et al., 2024)
		AI application (TD2)	
		Training need identification (TD3)	
		Performance improvement (TD4)	
Privacy and security	Q13 – Q16	Privacy personal information (PS1)	(Karamthulla et al., 2024; Rane et al., 2024)
		Privacy professional information (PS2)	
		Security personal information (PS3)	
		Security professional information (PS4)	
AI acceptance	Q17 – Q20	Trust (AIA1)	(Khair et al., 2020)
		Perceived benefit (AIA2)	
		Perceived improvement (AIA3)	
		Anticipation (AIA4)	
Position or level	Q4	• Ground-level employees (Software developer, IT support, QA tester, technician, system analyst, help desk executive etc.) • Lower- level manager (Team leader, team manager, junior project manager, coordinator, etc.) • Middle-level manager (Project manager, product manager, development manager, quality manager, etc.) • Upper-level manager (Chief technology officer, chief information officer, IT director, Brunch head, etc.)	IT industry labour market advertisements and job roles

4. FINDINGS

4.1. Reliability and Validity

After filtering out the incomplete and invalid responses, 216 responses have been considered for the analysis. The 16 items for 4 intended variables have been taken in exploratory factor analysis to evaluate the validity, whereas Table 2 shows that the KMO coefficient is 0.79. The KMO coefficient indicates that the sample size of this study is more than adequate for formulating the model to generate valid results. Bartlett's test showed that the chosen items for developing the model are significantly valid ($p < 0.05$).

Table 3. KMO Bartlett's test results for overall validity.

Kaiser-Meyer-Olkin measure of sampling adequacy.		**0.79**
Bartlett's test of sphericity	Approx. chi-square	4547.451
	Sig.	0.000

Table 3 presents the summary of KMO and Bartlett's test to examine whether the data fit the requirements of factor analysis. A KMO of 0.79 indicates satisfactory sampling adequacy, suggesting that the variables are sufficiently intercorrelated to permit factor analysis. Further, Bartlett's test of sphericity is significant ($\chi^2 = 4547.451$, $p < 0.001$), verifying that the correlation matrix is not an identity matrix. Collectively, these findings confirm the overall sufficiency of the dataset to carry out factor analysis.

Table 4. Item loadings, reliability and validity.

Factors	Factors and item loadings						
	1	2	3	4	AVE	CR	C alpha
AIA1 trust	0.980				0.873	0.953	0.951
AIA2 perceived benefit	0.930						
AIA3 perceived improvement	0.911						
AIA4 anticipation	0.915						
PS1 privacy personal information		0.976			0.888	0.958	0.958
PS2 privacy professional information		0.936					
PS3 security personal information		0.927					
PS4 security professional information		0.929					
TD1 AI awareness			0.977		0.886	0.958	0.957
TD2 AI application			0.934				
TD3 training need identification			0.938				
TD4 performance improvement			0.916				
TF1 transparency recruitment				0.974	0.908	0.967	0.966
TF2 transparency appraisal				0.947			
TF3 fairness recruitment				0.964			
TF4 fairness appraisal				0.925			

Table 4 explains the factor and item loadings. The following factor loadings were identified from the initial PLS-SEM model diagnosis. The loadings of each item indicate that the items are strongly associated with the intended variables. The validity of each scale or variable is high (AVE > 0.8), with a very high level of Composite Reliability (CR > 0.9) and high Internal Reliability (Cronbach's Alpha > 0.9).

4.2. Exploration of Variables

Table 5 shows that perceived transparency and fairness attributes of AI usage in HRM are currently below a moderate level, whereas the perceived fairness in appraisal (3.19±1.091) due to AI usage is at a moderate level. The training and development attributes regarding AI are currently above a moderate level in the IT industry, whereas the perceived effectiveness of AI-based training need identification is at a moderate level. Employees have moderate support for the idea that AI usage is for performance improvement, not for replacing employees (3.43±1.054). The perceived privacy and security attribute due to AI usage among employees is currently at a moderate level. Regarding acceptance of AI, employees highlighted a less than moderate level of trust (2.69±1.343) and a lower anticipation (2.64±1.007) of further AI adoption.

Table 5. Descriptive statistics of items.

Factors	Mean	SD	Q1(25%)	Median	Q3(75%)
TF1 transparency recruitment	2.54	1.192	2	2	3
TF2 transparency appraisal	2.85	1.104	2	3	4
TF3 fairness recruitment	2.94	1.18	2	3	4
TF4 fairness appraisal	3.19	1.091	2	3	4
TD1 AI awareness	3.57	1.203	3	4	5
TD2 AI application	3.54	1.157	3	4	4
TD3 training need identification	3.36	1.173	3	3	4
TD4 performance improvement	3.43	1.054	3	3	4
PS1 privacy personal information	3.19	1.165	2	3	4
PS2 privacy professional information	3.17	1.095	2	3	4
PS3 security personal information	2.94	1.081	2	3	4
PS4 security professional information	3.26	1.095	3	3	4
AIA1 trust	2.69	1.343	2	2	4
AIA2 perceived benefit	3.25	1.247	2	3	4
AIA3 perceived improvement	3.08	0.941	2	3	4
AIA4 anticipation	2.64	1.007	2	3	3

The following correlation matrix of latent variables within Table 6 shows that the perceived level of transparency and fairness is positively correlated with perceived privacy and security due to AI usage in HRM (r = 0.211). Perceived training and development aspects related to AI adaptation are also moderately and positively correlated with perceived privacy and security (r = 0.315). This indicates a higher sense of privacy and security because the usage of AI is low to moderate and is associated with a higher level of training and development effectiveness due to AI, as well as transparency and fairness in AI usage for HRM.

Table 6. Correlation between latent variables.

Sr. No.	Variables	1	2	3	4	5
1	AI acceptance	1	0.757*	-0.005	0.317*	0.267*
2	Position level	0.757	1	-0.058	0.224*	0.092
3	Privacy security	-0.005	-0.058	1	0.315	0.211*
4	Training development	0.317*	0.224*	0.315*	1	0.074
5	Transparency fairness	0.267*	0.092	0.211*	0.074	1

Note: *. Correlation is significant at the 0.05 level (2-tailed).

4.3. SEM-PLS Analysis

The following Figure 2 illustrates the SEM PLS model used for analysis, where the annotated values indicate the significance (p-value) of each relationship based on the bootstrapped results with a sample size of 50,000. The selected independent variables and moderators can predict 64.7% of the variability in AI acceptance among employees (R-square 0.647), indicating strong predictive power.

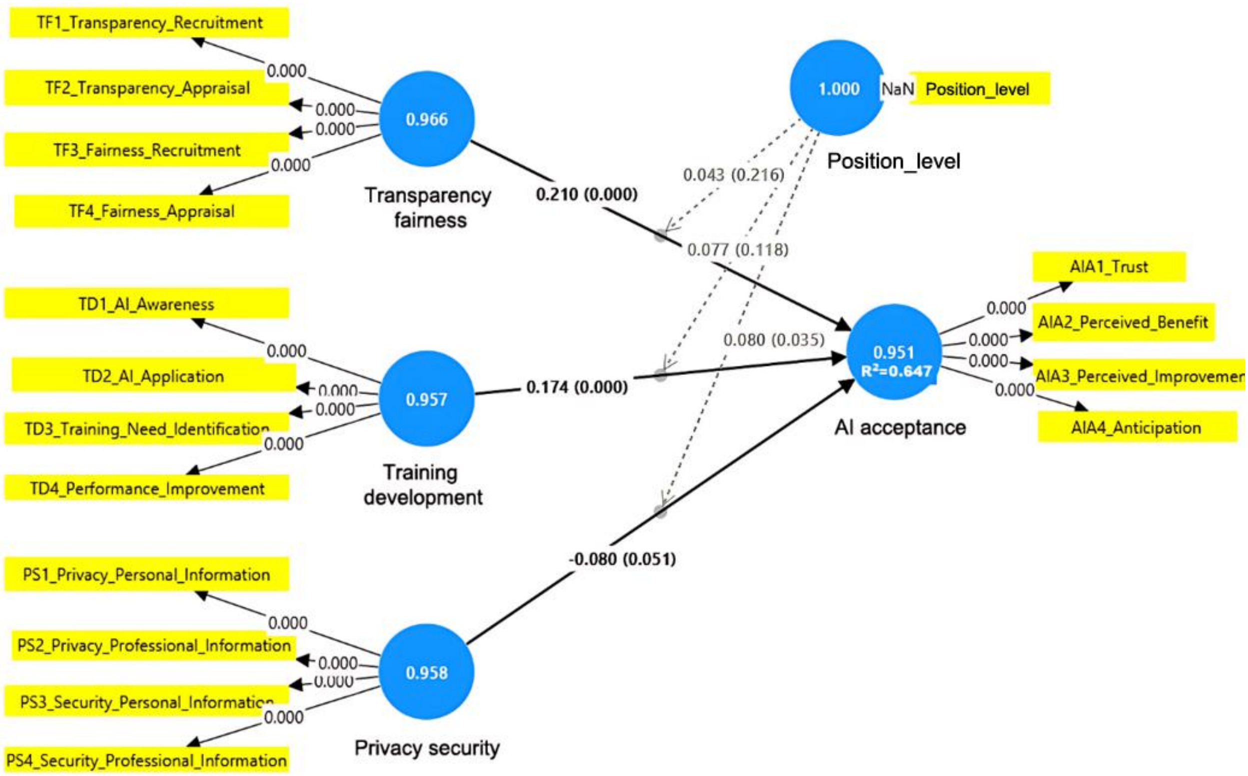

Figure 2. SEM-PLS Model in SMART PLS (Cronbach's Alpha, Path Coefficients, P-values)

According to Table 7, the strongest and most significant predictor of AI acceptance is the position or level of employees (B = 0.663, $p < 0.05$), indicating that employees in higher positions have significantly greater AI acceptance than those in lower positions. Perceived transparency and fairness in HRM (B = 0.21, $p < 0.05$) is the second most significant predictor with a positive effect size, suggesting that higher perceived transparency and fairness in AI utilization for HR management significantly increase AI acceptance among employees. Therefore, hypothesis H1 is supported. Training and development ($B = 0.171$, $p < 0.05$) also has a significant positive effect on AI acceptance, indicating that increased utilization of training and development related to AI enhances AI acceptance. Hypothesis H2 is supported. There is no strong significant relationship between privacy and security and AI acceptance, leading to the rejection of H3.

Table 7. Path coefficients of SEM-PLS model.

	Coeff(O)	Coeff(M)	STDEV	T-Stat	P values
Position level -> AI acceptance	0.658	0.663	0.033	19.698	**0.000**
Privacy security -> AI acceptance	-0.08	-0.078	0.041	1.955	0.051
Training development -> AI acceptance	0.174	0.171	0.044	3.935	0.000
Transparency fairness -> AI acceptance	0.21	0.21	0.04	5.311	0.000
Position level x Training development -> AI acceptance	0.077	0.074	0.049	1.565	0.118
Position level x Transparency fairness -> AI acceptance	0.043	0.04	0.035	1.238	0.216
Position level x Privacy security -> AI acceptance	0.08	0.084	0.038	2.109	0.035

Note: O. Original sample, M. Sample mean.

Moderation interference of Position and Level ($B = 0.08$, $p < 0.05$) is found to be significant only in the effect of perceived Privacy and Security on AI acceptance. Therefore, H6 is accepted. It indicates that employees with higher positions or levels have a stronger relationship between their perceived Privacy and Security in the use of AI and their level of acceptance of AI. The hypotheses H4 and H5 are rejected.

5. DISCUSSION

5.1. Hypothesis Testing

The SEM model indicates the following.

Table 8. Hypothesis testing table.

Hypothesis	Acceptance status
H1: Perceived transparency and fairness have a significant effect on the acceptance of AI-based employee management systems amongst employees working in the Australian IT industry.	Accepted
H2: Training and development have a significant effect on the acceptance of AI-based employee management systems amongst employees working in the Australian IT industry.	Accepted
H3: Employee privacy and security have a significant effect on the acceptance of AI-based employee management systems amongst employees working in the Australian IT industry.	Rejected
H4: Employee designation level has a moderating interference on the relationship between Transparency and fairness and the employee management system.	Rejected
H5: Employee designation level has a moderating interference on the relationship between Training and development and the employee management system.	Rejected
H6: Employee designation level has a moderating interference on the relationship between Employee privacy and security and the employee management system.	Accepted

Table 8 illustrates the results of hypothesis testing. The hypothesis results suggest that transparency and fairness (H1) and training and development (H2) significantly influence employee acceptance of AI-based management systems in the Australian IT sector. However, employee privacy and security (H3) did not show a significant effect. While designation level did not moderate the relationships in H4 and H5, it did significantly influence the relationship between privacy/security and AI acceptance in H6.

5.2. Hypotheses Relationship Justification with Literature Support

The findings of the study indicated that the most significant driver of acceptance of AI-based EM in the Australian IT industry is that it ensures CSR is perceived as transparent and fair. Such findings are supported by the studies conducted by Schmidt et al. (2020) and Chukwuka and Dibie (2024), which found that a higher degree of transparency in AI operations and greater adherence of AI to ethical standards enhance the acceptance of AI-integrated EM among employees. However, the current perceived levels of fairness and transparency regarding the use of AI for EM are found to be low among Australian IT employees. Furthermore, the concerned finding aligns with the results of Hetterich (2020), who highlighted that the risk of algorithm bias can result in discrimination and potentially reduce employee trust in fairness and transparency during performance evaluations. This indicates that, while employees currently lack trust in the degree of transparency and fairness AI can ensure, if they develop trust in the future, their acceptance of AI-integrated HRM will be high.

The second most significant driver of acceptance of AI-based EM in the Australian IT industry that ensures CSR includes Training and Development, indicating that higher utilization of training and development concerning AI increases AI acceptance. Existing literature supports these findings. For instance, Nyathani (2023) and Rane et al. (2024) have claimed that AI-related training and development sessions enhance employee confidence and reduce the fear of losing a job, along with providing them with a better understanding of how AI helps in performance management. Furthermore, previous studies have shown that relevant and meaningful training helps reduce employees' negative feelings towards new technological adaptations by enabling them to learn and understand how to use AI systems, which lowers their ambiguity (Brougham & Haar, 2020). Additionally, training and development sessions provided to employees to enhance their knowledge of AI are effective in the Australian IT sector. This indicates that, as CSR initiatives targeted at employees, training and development are a key factor behind the current level of acceptance of AI integration in EM among staff. Further improvement of training and development related to AI could increase the degree of acceptance.

However, when it came to employee privacy and security, this study found that there is no significant relationship between privacy and security and employee acceptance of AI integration in EM systems in Australian IT sectors. These findings contradict existing literature, which highlights the perceived risks of privacy and security, as AI integration lowers employee acceptance of AI-integrated EM (Karamthulla et al., 2024; Rane et al., 2024). This is because previous studies have found a significant positive relationship between privacy and security and AI acceptance, which contradicts the current findings. The perceived privacy and security risk among Australian IT sector employees is moderate. Therefore, this study offers a unique finding that cannot be found in existing literature.

Irrespective of the moderation effect, the positional level of Australian IT sector employees is a driver of higher AI acceptance, which implies that employees in higher positions have greater acceptance of AI, while employees in lower positions have less confidence. Velanganni and Bhuvaneswari (2024), Choi (2021), and Madan and Ashok (2023) supported these findings, highlighting that higher-level employees have higher acceptance since they have a better understanding of AI usage for appraisal procedures and the ability to reduce their workload using AI-integrated EM.

However, the positional level does not have any impact on AI acceptance based on the transparency and fairness of the AI-integrated EM system. Similarly, the driving force for training and development on AI acceptance does not differ based on the position or level of the employees. This means the degree of acceptance among Australian IT employees of all levels can be enhanced if their perceived transparency and fairness of the AI-integrated EM system are improved. Additionally, effective training and development sessions on AI can enhance the understanding, confidence, and trust of both higher- and lower-level employees regarding how the AI-integrated EM system functions. However, this study indicated that employees with higher positions or levels have a stronger relationship between their perceived privacy and security in the usage of AI and their level of acceptance of the AI-integrated EM system. Velanganni and Bhuvaneswari (2024) and Madan and Ashok (2023) highlighted that higher-level employees are often involved in the process of AI-integrated employee performance management, which makes it easier for them to have an effective understanding of the degree of privacy and security of the system, unlike lower-level employees. Additionally, AI-driven EM systems are less likely to threaten the roles of higher-level employees since leadership roles require judgment and creativity beyond AI's capability. Hence, these can be the possible reasons behind the higher acceptance of AI-integrated EM systems amongst higher-level employees of the Australian IT sector compared to lower-level employees.

5.3. Limitations of the Research

The first limitation of this study is that it is entirely based on the reflective opinions of employees and has not measured behavioral acceptance. Additionally, no observational data has been used to evaluate the results of the study. Second, the study has not considered confounding factors that could influence the relationship between dependent and independent variables, such as organizational structure and external factors like the availability of technology and facilitation. Finally, this study is not generalized to all industries but has only focused on the Australian IT industry. Aside from these, there are no major limitations to this study.

6. CONCLUSION

6.1. Overall Findings

This study was conducted to assess the key drivers of acceptance of AI-based EM across various levels of employees working in the Australian IT industry. The study demonstrates that perceived transparency and fairness regarding AI-integrated EM enhance their acceptance of the same. Additionally, training and development, where AI-initiated sessions help employees understand the system and reduce fears of job loss across employee levels. Surprisingly, privacy and security risks do not appear to influence AI acceptance, contrary to existing literature. Higher-level positions correlate with greater acceptance of AI, as older employees understand its purpose in appraisal and workload reduction, ensuring their jobs are less likely to be replaced by automation. Nevertheless, acceptance could be improved if transparency and fairness in training and development initiatives—second only to higher positional levels—are enhanced. These findings offer valuable insights into AI integration in HRM, particularly for CSR-driven strategies.

6.2. Theoretical and Practical Implications

This study has contributed to the existing literature by offering new insights related to AI acceptance among employees through the lenses of theories such as the Technology Acceptance Model (TAM), Resource Dependence Theory (RDT), and the Theory of Innovation Diffusion (TID). The findings of this study have added to the existing knowledge of TAM by demonstrating how factors like fairness, transparency, and training impact the ease of usability and perceived usefulness of AI-based employee management systems. Furthermore, the findings of this study align with RDT by showing how organizations can integrate AI-driven employee management by relying on employee trust and skills while reducing perceived risks related to privacy and security. Finally, this study contributes to TID by illustrating how innovation adoption can be influenced by organizational position levels.

Concerning the managerial implications of the study, the findings emphasize prioritizing the implementation of AI in employee management systems in an ethical manner to ensure fairness and transparency, which can eventually contribute to the optimized benefits of the system for both employees and the organization. Additionally, contemporary managers must redesign their training and development strategies so that both managers and employees can be trained effectively and in a personalized manner to increase accuracy, improve understanding of the automated system, and foster higher acceptance among employees. Furthermore, organizational managers must shift their attention toward employee privacy and security to foster a culture of trust and develop HR policies that help balance automation with human oversight. This approach can help make AI an enhancer rather than a disruptor of HRM functions.

6.3. Future Scope

The findings of this study have effectively addressed the key gaps. The results have the potential to challenge prior findings and assumptions related to privacy, security concerns, and the acceptance of AI. It offers new insights into the transformation of HRM functions through increased acceptance of AI. However, there is scope for future research in this area. Future studies can explore other geographic regions and industries and incorporate qualitative perceptions to develop a contextual understanding of the key motives behind AI acceptance or rejection behavior.

Funding: This study received no specific financial support.
Institutional Review Board Statement: The Ethical Committee of the Dankook University, Korea has granted approval for this study on 2 March 2024.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: The corresponding author can provide the supporting data of this study upon a reasonable request.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Both authors contributed equally to the conception and design of the study. Both authors have read and agreed to the published version of the manuscript.

REFERENCES

Abhari, K., Bhullar, A., Le, J., & Sufi, N. (2023). Advancing employee experience management (EXM) platforms. *Strategic HR Review, 22*(3), 102-107. https://doi.org/10.1108/SHR-04-2023-0021

Arslan, A., Cooper, C., Khan, Z., Golgeci, I., & Ali, I. (2022). Artificial intelligence and human workers interaction at team level: A conceptual assessment of the challenges and potential HRM strategies. *International Journal of Manpower, 43*(1), 75-88. https://doi.org/10.1108/IJM-01-2021-0052

Behn, O., Leyer, M., & Iren, D. (2024). Employees' acceptance of AI-based emotion analytics from speech on a group level in virtual meetings. *Technology in Society, 76*, 102466. https://doi.org/10.1016/j.techsoc.2024.102466

Brougham, D., & Haar, J. (2020). Technological disruption and employment: The influence on job insecurity and turnover intentions: A multi-country study. *Technological Forecasting and Social Change, 161*, 120276. https://doi.org/10.1016/j.techfore.2020.120276

Budhwar, P., Malik, A., De Silva, M. T., & Thevisuthan, P. (2022). Artificial intelligence–challenges and opportunities for international HRM: A review and research agenda. *The International Journal of Human Resource Management, 33*(6), 1065-1097. https://doi.org/10.1080/09585192.2022.2035161

Choi, Y. (2021). A study of employee acceptance of artificial intelligence technology. *European Journal of Management and Business Economics, 30*(3), 318-330. https://doi.org/10.1108/EJMBE-06-2020-0158

Chukwuka, E. J., & Dibie, K. E. (2024). Strategic role of artificial intelligence (AI) on human resource management (HR) employee performance evaluation function. *International Journal of Entrepreneurship and Business Innovation, 7*(2), 269-282. https://doi.org/10.52589/IJEBI-HET5STYK

Connelly, C. E., Fieseler, C., Černe, M., Giessner, S. R., & Wong, S. I. (2021). Working in the digitized economy: HRM theory & practice. *Human Resource Management Review, 31*(1), 100762. https://doi.org/10.1016/j.hrmr.2020.100762

Decramer, A., Smolders, C., & Vanderstraeten, A. (2013). Employee performance management culture and system features in higher education: relationship with employee performance management satisfaction. *The International Journal of Human Resource ManagemenT, 24*(2), 352-371. https://doi.org/10.1080/09585192.2012.680602

Ganatra, N. J., & Pandya, J. D. (2023). The transformative impact of artificial intelligence on hr practices and employee experience: A review. *Journal of Management Research and Analysis, 10*(2), 106-111. https://doi.org/10.18231/j.jmra.2023.018

Gandía, J. A. G., Gavrila, S. G., de Lucas Ancillo, A., & del Val Núñez, M. T. (2025). Towards sustainable business in the automation era: Exploring its transformative impact from top management and employee perspective. *Technological Forecasting and Social Change, 210*, 123908. https://doi.org/10.1016/j.techfore.2024.123908

Gao, S., & Segumpan, R. G. (2024). The effect of AI-driven talent management on organizational performance among retail SMEs: A systematic review. https://doi.org/10.5171/2024.588377

Hansen, J. M., McDonald, R. E., & Hatfield, H. (2023). Exploring market orientation versus finance orientation effects on perceived CSR motivations and outcomes using resource-advantage (RA) theory. *Journal of Business Research*, *164*, 113977. https://doi.org/10.1016/j.jbusres.2023.113977

Heinfeldt, J., & Curcio, R. (1997). Employee management strategy, stakeholder-agency theory, and the value of the firm. *Journal of Financial and Strategic Decisions*, *10*(1), 67-75.

Hetterich, L. C. (2020). *The role of the psychological factor trust for the rejection of AI services vs human-based services in hospitality*. Master's Dissertation, NOVA Information Management School.

Karamthulla, M. J., Tadimarri, A., Tillu, R., & Muthusubramanian, M. (2024). Navigating the future: AI-driven project management in the digital era. *International Journal for Multidisciplinary Research*, *6*(2), 1-11.

Khair, M. A., Mahadasa, R., Tuli, F. A., & Ande, J. (2020). Beyond human judgment: Exploring the impact of artificial intelligence on HR decision-making efficiency and fairness. *Global Disclosure of Economics and Business*, *9*(2), 163-176. https://doi.org/10.18034/gdeb.v9i2.730

Kok, J. N., Boers, E. J., Kosters, W. A., Van der Putten, P., & Poel, M. (2009). Artificial intelligence: Definition, trends, techniques, and cases. *Artificial Intelligence*, *1*(270-299), 51.

Madan, R., & Ashok, M. (2023). AI adoption and diffusion in public administration: A systematic literature review and future research agenda. *Government Information Quarterly*, *40*(1), 101800.

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, *120*, 262-273.

Masum, A., Aziz, H., & Hassan, M. (2020). Corporate social responsibility and its effect on community development: An overview. *Journal of Accounting Science*, *22*(1), 35-40.

Mensah, G. B. (2023). Artificial intelligence and ethics: a comprehensive review of bias mitigation, transparency, and accountability in AI Systems. *Preprint, November*, *10*(1). https://doi.org/10.62839/ajfra/2024.v1.i1.32-45

Moon, J. (2007). The contribution of corporate social responsibility to sustainable development. *Sustainable development*, *15*(5), 296-306. Https://Doi.Org/10.1002/Sd.346

Nyathani, R. (2023). AI-enabled learning and development: Hr's new paradigm. *Journal of Marketing & Supply Chain Management*, *2*(2), 1-5. https://doi.org/10.47363/JMSCM/2023(2)117

Prikshat, V., Islam, M., Patel, P., Malik, A., Budhwar, P., & Gupta, S. (2023). AI-Augmented HRM: Literature review and a proposed multilevel framework for future research. *Technological Forecasting and Social Change*, *193*, 122645. https://doi.org/10.1016/j.techfore.2023.122645

Rane, N., Choudhary, S. P., & Rane, J. (2024). Acceptance of artificial intelligence: Key factors, challenges, and implementation strategies. *Journal of Applied Artificial Intelligence*, *5*(2), 50-70. https://doi.org/10.48185/jaai.v5i2.1017

Schmidt, P., Biessmann, F., & Teubner, T. (2020). Transparency and trust in artificial intelligence systems. *Journal of Decision Systems*, *29*(4), 260-278.

Velanganni, R., & Bhuvaneswari, S. (2024). The role of artificial intelligence in transforming human resource management. *Library Progress International*, *44*(3), 11545-11551.

Wang, P. (2019). On defining artificial intelligence. *Journal of Artificial General Intelligence*, *10*(2), 1-37. https://doi.org/10.2478/jagi-2019-0002

Yanamala, K. K. R. (2020). Ethical challenges and employee reactions to AI adoption in human resource management. *International Journal of Responsible Artificial Intelligence*, *10*(8), 1-13.

Yang, J., Blount, Y., & Amrollahi, A. (2024). Artificial intelligence adoption in a professional service industry: A multiple case study. *Technological Forecasting and Social Change*, *201*, 123251. https://doi.org/10.1016/j.techfore.2024.123251

Appendix 1. The survey questionnaire used to collect primary data.

Appendix 1 presents the survey questionnaire used to collect primary data.

*************Survey Questionnaire*************

1. What is your gender?

2. What is your age group?

3. How much experience do you have?

Less than 1 year

1 to 5 years

5 to 10 years

10 to 20 years

More than 20 years

4. What is your existing position or level of employment or work involvement?

- Ground-level employees (Software Developer, IT Support, QA Tester, Technician, System Analyst, Help Desk Executive, etc.)
- Lower-Level Manager (Team Leader, Team Manager, Junior Project Manager, Coordinator, etc.)
- Middle Level Manager (Project Manager, Product Manager, Development Manager, Quality Manager, etc.)
- Upper-Level Manager (Chief Technology Officer, Chief Information Officer, IT Director, Branch Head, etc.)

Kindly rate the following statement from 1 to 5 as per your experience and opinion regarding the transparency and fairness of the HR management system within your company in terms of their usage of AI. (1= Highly Disagree, 5 = Highly Agree)

5. The level of AI utilization in recruitment and selection by HR Management is transparently communicated to all employees.

6. The level of AI utilization in employee performance evaluation, appraisal, or promotion is transparently communicated to all employees.

7. The data-driven model of AI for candidate selection and recruitment is fairer in terms of bias, discrimination, and ethical standards than the traditional manual procedure.

8. The data-driven model of AI for employee performance evaluation, appraisal, and promotion is fairer in terms of bias, discrimination, and ethical standards than traditional manual procedures.

Kindly rate the following statement from 1 to 5 as per your experience and opinion regarding the training and development provided by your organization for the implementation of AI. (1= Highly Disagree, 5 = Highly Agree).

9. The employer provides awareness training regarding AI utilization and its benefits in organizational operations.

10. The pieces of training and development are provided regarding the application and utilization of AI tools and techniques for work procedures.

11. The AI-driven system is appropriately able to identify training and development needs by the employee for employee performance improvement.

12. In your organization, AI is used to improve employee performance, not to replace employees with AI.

Kindly rate the following statement from 1 to 5 based on your experience and opinion regarding employee privacy and security maintained by your organization, considering AI usage in your organization (1=Highly Disagree, 5=Highly Agree).

13. The AI-driven procedure implemented in your organization is capable of preserving privacy and confidentiality while handling sensitive personal information of employees, such as addresses, personal lives, dates of birth, contacts, personal health, etc.

14. The AI-driven procedure implemented in your organization is capable of preserving privacy and confidentiality while handling sensitive professional information of employees, such as salaries, performance scores, compensations, disciplinary records, etc.

15. AI-driven technologies implemented in your organization are capable of ensuring the security of personal and professional information from any unauthorized access and security breach done within the organization.

16. AI-driven technologies implemented in your organization are capable of ensuring the security of personal and professional information from any security breach or cybercriminal activity from external sources.

Kindly rate the following statement from 1 to 5 based on your experience and opinion regarding your acceptance of AI usage in HR management within your organization (1=Highly Disagree, 5=Highly Agree).

17. I trust the utilization of AI in the HR operations of my organization.

18. I think AI application in HR management can have beneficial outcomes for me as an employee.

19. I believe that AI implementation in HR management can enhance and improve the capabilities and overall quality of HR systems and their operations compared to traditional or manual HR management systems.

20. I look forward to further AI implementation in HR management and operation.