

Acceptance of AI-based human resource practices: Sectoral differences between technology-intensive and traditional industries

Yapay zekâ temelli insan kaynakları uygulamalarının kabulü: Teknoloji yoğun ve geleneksel sektörler arasında karşılaştırmalı bir analiz

Selma Kalkavan¹ 

¹PhD., Independent Researcher, İstanbul, Türkiye



Citation:

Kalkavan, S. (2026). Acceptance of AI-based human resource practices: Sectoral differences between technology-intensive and traditional industries. *OPUS- Journal of Society Research*, 23, e1991347.
<https://doi.org/10.26466/opusjsr.1991347>

Open Access Statement:

This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). This license permits unrestricted use, distribution, and reproduction in any medium, provided that the original author(s) and the source are properly credited. The original publication in *OPUS Journal of Society Research* must be cited in accordance with accepted academic practice.

Review Note:

Evaluated by Double-Blind Peer Review

Ethics Reporting:

To report potential ethical concerns, contact: editorialoffice@opusjournal.net

Similarity screening was conducted via intihal.net.



Abstract

This study examines employee acceptance of AI-based human resource management practices in technology-intensive and traditional sectors. Data were collected from 360 employees, with 60 participants from each of six sectors. Biotechnology, information technology, and manufacture of computer, electronic and optical products formed the technology-intensive group, while retail, textiles, and hotels formed the traditional group. Acceptance was evaluated across recruitment, performance appraisal, training planning, and talent management. The explanatory variables were perceived usefulness, perceived ease of use, trust in AI, perceived algorithmic fairness and transparency, and loss of human touch. The subgroup regressions show that usefulness, ease of use, and trust positively predict acceptance in technology-intensive sectors. In traditional sectors, fairness and transparency positively predict acceptance, while loss of human touch negatively predicts acceptance. Five significant interactions identify specific differences between sector groups. The positive association of fairness and transparency with acceptance is stronger in traditional sectors for recruitment and performance appraisal, and the negative association of loss of human touch is stronger in traditional sectors for recruitment. The positive association of trust is stronger in technology-intensive sectors for training planning, while that of usefulness is stronger in technology-intensive sectors for talent management. Acceptance is descriptively higher in training planning and talent management than in recruitment and performance appraisal. These findings show that employee evaluations of AI-based HR practices vary by sector group and HR function, supporting attention to usefulness, trust, fairness, and human involvement in the particular functions where their associations with acceptance differ.

Keywords: Artificial intelligence, human resource management, technology acceptance

Öz

Bu araştırmanın amacı, yapay zekâ temelli insan kaynakları uygulamalarının çalışanlar tarafından kabul düzeyinin teknoloji yoğun ve geleneksel sektörlerde nasıl farklılaştığını incelemektir. Araştırmada teknoloji yoğun grupta biyoteknoloji, bilişim teknolojileri ve bilgisayar, elektronik ve optik ürünlerin imalatı, geleneksel grupta ise perakende, tekstil ve otelcilik sektörleri ele alınmıştır. Her sektörden 60 katılımcı olmak üzere toplam 360 çalışandan veri toplanmıştır. Çalışmada yapay zekâ kabulü işe alım, performans değerlendirme, eğitim planlama ve yetenek yönetimi fonksiyonları açısından ayrı ayrı değerlendirilmiştir. Algılanan fayda, algılanan kullanım kolaylığı, yapay zekâyâ güven, algılanan algoritmik adalet ve şeffaflık ile insan temasının kaybı temel değişkenler olarak incelenmiştir. Alt grup regresyonları, teknoloji yoğun sektörlerde algılanan fayda, algılanan kullanım kolaylığı ve yapay zekâyâ güvenin kabulü pozitif yönde yordadığını göstermektedir. Geleneksel sektörlerde algılanan adalet ve şeffaflık kabulü pozitif, insan temasının kaybı ise negatif yönde yordamaktadır. Beş anlamlı etkileşim, sektör grupları arasındaki farklılıkları ortaya koymaktadır. Algılanan adalet ve şeffaflığın kabulü pozitif ilişkisi işe alım ve performans değerlendirmede, insan temasının kaybının negatif ilişkisi ise işe alımda geleneksel sektörlerde daha güçlüdür. Yapay zekâyâ güvenin eğitim planlamadaki pozitif ilişkisi ve algılanan faydanın yetenek yönetimindeki pozitif ilişkisi teknoloji yoğun sektörlerde daha güçlüdür. Eğitim planlama ve yetenek yönetimi fonksiyonlarında kabul düzeyinin genel olarak daha yüksek olduğu, işe alım ve performans değerlendirme süreçlerinde ise etik, adalet ve insan denetimi beklentilerinin daha belirgin hale geldiği görülmektedir. Araştırma sonuçları, yapay zekâ temelli İK uygulamalarının kabulünün sektör grubu ve İK fonksiyonuna göre farklılaştığını göstermektedir. Bu bulgular, fayda, güven, adalet ve insan temasının ilgili fonksiyondaki kabulle ilişkileri doğrultusunda değerlendirilmesini desteklemektedir.

Anahtar Kelimeler: Yapay zekâ, insan kaynakları yönetimi, teknoloji kabulü

Introduction

Over the past few years, artificial intelligence (AI) has shifted from an experimental technology to an organizational capability that increasingly shapes the redesign of business processes. In 2025, approximately one in five businesses in the European Union used AI technologies, with adoption reaching 55.0% among large enterprises and 62.5% in the information and communication sector (Eurostat, 2026). At the employee level, 58% of workers globally reported using AI tools intentionally and regularly in their jobs (Gillespie et al., 2025). This diffusion is particularly visible in human resource management (HRM), where data-intensive processes combine repetitive operational tasks with managerial decisions that require interpretation. Accordingly, AI is being used in recruitment, performance appraisal, training and development planning, talent management, internal mobility and workforce analytics to improve efficiency, standardization, personalization and predictive capacity (Gong et al., 2025; Tusquellas et al., 2024; Yıldız, 2025).

However, the adoption of AI in HRM cannot be reduced to technical modernization. Bias in recruitment algorithms, surveillance concerns in performance appraisal, data privacy risks, and opaque decision-making processes have made fairness, transparency, accountability, and human oversight central to employee acceptance (Rauhala et al., 2026; Rigotti & Fosch-Villaronga, 2024). Recent findings also indicate that employees generally prefer AI to support rather than replace human judgment in consequential organizational decisions (CIPD, 2025). Therefore, the organizational implementation of an AI system does not necessarily ensure its effective use. Employees must also perceive the system as useful, understandable, trustworthy, and legitimate.

The Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology explain adoption through factors such as perceived usefulness, perceived ease of use, performance expectancy, social influence, and facilitating conditions (Davis, 1989; Venkatesh et al.,

2003). Yet AI-based applications require a broader framework because employees also evaluate their explainability, procedural fairness, potential threat, and effects on autonomy and human interaction (Chen et al., 2025; Nguyen et al., 2026). These evaluations may vary across organizational contexts. Technology-intensive sectors generally possess stronger digital infrastructures, higher levels of AI exposure, and workforces with more advanced digital skills, whereas traditional sectors often adopt AI more gradually and under greater uncertainty (Eurostat, 2026; Kergroach & Heritier, 2025).

Despite the growing literature, most studies focus on a single HR function, sector, or organizational setting. Consequently, it remains unclear whether employees in technology-intensive and traditional sectors evaluate AI-based HR practices through the same acceptance mechanisms and whether these mechanisms differ across recruitment, performance appraisal, training planning, and talent management (Gong et al., 2025; Savolainen et al., 2026). Addressing this gap, the present study compares three technology-intensive and three traditional sectors using data collected from 360 employees, with 60 participants from each sector. AI acceptance is examined separately across four HR functions, together with perceived usefulness, perceived ease of use, trust in AI, perceived algorithmic fairness and transparency, and perceived loss of human touch. In this way, the study evaluates AI acceptance as a sector- and function-specific organizational phenomenon rather than as a general attitude toward technology.

Within this framework, the study addresses the following research questions:

RQ1. How do employee acceptance levels for AI-based practices vary across the technology-intensive and traditional sector groups and the four HR functions of recruitment, performance appraisal, training planning, and talent management?

RQ2. How are perceived usefulness, perceived ease of use, trust in AI, perceived algorithmic fairness and transparency, and perceived loss of human touch related to AI acceptance within each sector group and HR function?

RQ3. How do the patterns of association between the five explanatory variables and AI acceptance compare between technology-intensive and traditional sectors across the four HR functions?

Artificial Intelligence Transformation in Human Resources Management and Core Functional Applications

The use of artificial intelligence in human resources management initially focused on automating repetitive and standardized tasks. As analytical and personalization capabilities developed, however, AI applications began to support managerial decision-making and increasingly became integrated into strategic human resources processes (Ubeda-Garcia et al., 2025). Recruitment, performance appraisal, training planning, and talent management represent four major areas in which this transformation has become particularly visible. Although AI can enhance efficiency, consistency, and predictive capacity across these functions, its acceptance depends on the characteristics and perceived consequences of each application.

Recruitment is among the earliest and most visible areas of AI use in human resources management. Resume-screening algorithms, recruitment chatbots, and automated interview analysis systems can process large applicant pools, standardize initial evaluations, and reduce the time and costs associated with candidate selection (Köchling & Wehner, 2020; Naim et al., 2015). These technologies are often introduced with the expectation that data-driven assessment will improve efficiency and objectivity. Nevertheless, AI-supported recruitment also raises concerns regarding algorithmic bias, data quality, transparency, accountability, and the limited capacity of automated systems to recognize contextual and interpersonal nuances. Candidates may perceive such systems as useful and convenient while questioning their accuracy, comprehensiveness, and ability to reproduce human judgment (Dadaboyev et al., 2025). Therefore, acceptance in recruitment depends on whether AI is perceived as fair, explainable, and

subject to meaningful human oversight rather than solely on its operational efficiency (Bujold et al., 2024).

In performance appraisal, AI enables organizations to move from periodic evaluations toward systems based on continuous data collection, monitoring, and feedback. Algorithmic tools can integrate multiple performance indicators, identify behavioral patterns, and generate standardized assessments. From an organizational perspective, these capabilities may reduce subjectivity and support more consistent evaluations. From the employee perspective, however, continuous algorithmic assessment may also intensify perceptions of surveillance, control, and reduced autonomy. Research indicates that the effects of algorithmic performance evaluation depend on how employees interpret the system's accuracy, fairness, transparency, and influence on their professional discretion (Ali et al., 2026). Consequently, acceptance is likely to decrease when AI is perceived as replacing managerial judgment or producing consequential evaluations through decision-making procedures that employees cannot understand or challenge.

The contribution of AI to training planning and employee development is primarily associated with personalization. AI-based tools can identify skill gaps, assess development needs, recommend relevant content, create individualized learning paths, and provide real-time feedback. These applications allow organizations to replace standardized training programs with learning systems that are more closely aligned with employees' roles, competencies, and future development requirements. Compared with recruitment and performance appraisal, training applications generally involve fewer direct risks concerning employment decisions or formal evaluation. Employees may therefore be more willing to accept AI when it is positioned as a developmental resource that supports learning and job performance. Nevertheless, positive outcomes depend on employees' ability to use these systems effectively. Training, digital competence, and organizational support remain important because the perceived benefits of AI are

more likely to emerge when employees possess the skills required to interpret and apply its recommendations (Tusquellas et al., 2024).

In talent management, AI extends beyond the assessment of current employee performance by supporting predictions about future workforce needs. Talent management practices seek to identify strategically important positions, recognize high-potential employees, develop internal talent pools, and retain employees who contribute to sustainable organizational advantage (Collings & Melahi, 2009; Lewis & Heckman, 2006). AI can support these objectives by analyzing employee engagement, identifying internal mobility opportunities, forecasting turnover, classifying talent pools, and predicting future skill requirements. Such applications position AI as a strategic decision-support infrastructure rather than as a simple operational filtering mechanism. However, predictive talent management systems remain sensitive to data quality, algorithmic bias, explainability and the possibility that employees may be categorized through criteria that are not visible to them. Accordingly, employees may regard AI-supported talent management as beneficial while expecting its recommendations to remain open to review, contextual interpretation, and human intervention.

Overall, AI does not have an identical meaning across human resources functions. Recruitment and performance appraisal directly affect selection, evaluation, and career outcomes and are therefore more sensitive to fairness, transparency, accountability, and the preservation of human judgment. Training planning and talent management may generate comparatively higher acceptance when employees perceive them as supportive, developmental, and future-oriented. This functional variation indicates that employee acceptance should be evaluated according to the specific organizational decisions in which AI is used and the degree of risk, control, and human involvement associated with those decisions.

Technological Acceptance Models and Employees' Perceptions of Artificial Intelligence

The Technology Acceptance Model provides a foundational framework for explaining employees' acceptance of AI-based human resources applications. According to the model, perceived usefulness and perceived ease of use are the primary determinants of technology adoption (Davis, 1989). Employees are therefore more likely to accept AI-based systems when they believe that these applications improve their performance, simplify work processes, and require limited effort to use. The Unified Theory of Acceptance and Use of Technology extends this perspective by incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions into the adoption process (Venkatesh et al., 2003). Within the HR context, these models indicate that acceptance depends on both the perceived functionality of AI and the organizational conditions supporting its use, including training, managerial support, and integration into existing work processes.

However, AI-based applications differ from conventional information systems because they can generate predictions, recommendations, and decisions that directly affect employees' careers and working conditions. For this reason, perceived usefulness and ease of use alone may not adequately explain their acceptance. Trust has emerged as a particularly important determinant, reflecting employees' willingness to rely on AI-generated evaluations and recommendations. Research indicates that trust is closely associated with perceived usefulness and behavioral intention, while concerns regarding fairness, privacy, and accountability can weaken employees' willingness to rely on AI systems (Choung et al., 2023; Seo & Lee, 2021). These concerns are especially relevant in HR processes because algorithmic decisions may influence recruitment, performance appraisal, development opportunities, and internal mobility.

Perceived fairness and transparency also shape whether AI-based HR applications are regarded as

legitimate. Although algorithmic systems are frequently introduced with expectations of greater efficiency and objectivity, their acceptance may decline when employees believe that the underlying data, evaluation criteria, or decision rules reproduce discrimination or cannot be questioned (Köchling & Wehner, 2020). Transparency can support trust by making the logic of AI-generated decisions more understandable and controllable. Nevertheless, its effects may not always be uniformly positive. Greater information about automated decision-making can strengthen perceptions of fairness while simultaneously increasing anxiety about surveillance, reduced autonomy, or replacement by technology (Yu & Li, 2022). Thus, transparency is most likely to support acceptance when it is accompanied by accountability, opportunities for review, and meaningful human oversight.

Employee perceptions are also influenced by the potential effects of AI on job security, professional identity, and human interaction. Anxiety may arise from the possibility of job displacement as well as from pressure to acquire new skills and adapt to changing work requirements. Such concerns can contribute to emotional exhaustion and reduce employees' engagement with AI-supported work processes (Chen et al., 2025). Similarly, employees who perceive smart technologies, robotics, and algorithms as threats to their occupational future may report lower organizational commitment and career satisfaction, alongside higher turnover intentions and cynicism (Brougham & Haar, 2018). Acceptance may therefore decline when AI is interpreted as replacing human expertise, weakening employee autonomy, or reducing interpersonal involvement in consequential organizational decisions.

These findings suggest that employee acceptance of AI-based HR practices involves both instrumental and ethical evaluations. Perceived usefulness and ease of use explain whether a system is regarded as functional and manageable, whereas trust, fairness, transparency, and the preservation of human involvement determine whether it is perceived as legitimate and appropri-

ate. Accordingly, AI acceptance in human resources management should be understood as a multidimensional process shaped by performance expectations, organizational support, perceived control, professional security, and the extent to which human judgment remains embedded in decision-making processes (Golgeci et al., 2025).

Sectoral Context of AI Adoption: Technology-Intensive and Traditional Sectors

The adoption and acceptance of artificial intelligence are shaped by the digital maturity, workforce capabilities, and organizational readiness of different sectors. Technology-intensive sectors generally provide a more favorable environment for the integration of AI-based human resources applications because employees in these sectors are more frequently exposed to digital technologies and data-driven work processes. The OECD's sectoral AI intensity classification indicates that information technology services, media, and telecommunications display relatively high levels of AI-related human capital, innovation, exposure, and use, whereas sectors such as textiles, construction, and hospitality exhibit lower levels of AI intensity (OECD, 2024). This distinction suggests that AI is more likely to be perceived as an extension of existing organizational infrastructure in technology-intensive sectors, while it may be experienced as a less familiar and more disruptive innovation in traditional sectors.

Organizational adoption indicators support this sectoral distinction. In 2025, the information and communication sector recorded the highest rate of AI use in the European Union, reaching 62.52%, while adoption remained below 25% in many other economic activities (Eurostat, 2026). Technology-intensive sectors also make greater use of relatively advanced AI applications, including natural language generation, text mining, and audiovisual content generation. More frequent interaction with such tools may increase employees' familiarity with algorithmic systems and strengthen their perceptions of the usefulness and legitimacy of similar

applications in HR processes. However, this relationship should not be interpreted as automatic acceptance. Even in digitally mature sectors, concerns regarding job displacement, data use, work intensity, wage pressure, and insufficient oversight continue to influence employee responses to AI (OECD, 2024).

Workforce characteristics constitute another important source of sectoral variation. Technology-intensive sectors generally place greater organizational value on digital literacy, data interpretation, problem-solving, and creative skills. Although advanced technical expertise is required only for a limited group of employees, a broader set of hybrid skills is necessary for workers to use AI systems effectively and interpret their outputs (OECD, 2026). Employees who possess these capabilities may be more likely to perceive AI as a performance-enhancing resource rather than as a threat. Consequently, perceived usefulness, ease of use, and trust may assume greater importance in technology-intensive sectors, where employees are already accustomed to evaluating technologies according to their functional contribution to work processes.

In traditional sectors, by contrast, AI adoption tends to progress more gradually and unevenly (Calvino et al., 2024). Construction, transportation, warehousing, textiles, and other operationally intensive sectors frequently face limitations involving digital infrastructure, investment capacity, relevant expertise, and organizational readiness. Eurostat data indicate that a lack of appropriate expertise is among the most frequently reported barriers for firms that have considered adopting AI but have not yet implemented it. Legal uncertainty, data protection concerns, and privacy risks also constrain adoption (Eurostat, 2026). These barriers are particularly significant for small and medium-sized enterprises, where limited financial resources and digital capabilities may restrict the implementation of AI technologies (OECD, 2024).

The organization of work in traditional sectors can further affect how employees interpret AI-based HR practices. Business processes in these sectors often depend on physical production, face-

to-face coordination, direct supervision, and practical experience. Under such conditions, employees may find it more difficult to identify the immediate value of AI or may regard its implementation as incompatible with established work routines. Research on manufacturing and production environments indicates that concerns about job loss and the pressure to acquire new skills can reduce employee engagement and intensify resistance to AI-supported transformation (Chen et al., 2025). Studies of textiles, manufacturing firms, and SMEs similarly show that digital transformation is frequently implemented through gradual, pilot-based initiatives and is shaped by technology costs, skill shortages, implementation risks, and organizational preparedness (Bertola & Teunissen, 2018; Mittal et al., 2018; Moeuf et al., 2018).

Concerns regarding the loss of human involvement may also be more pronounced in traditional sectors. Although employees and HR professionals may recognize the efficiency and standardization benefits of AI, they may simultaneously perceive automated systems as less reliable, less sensitive to contextual differences, and less capable of reproducing human judgment (Horodyski, 2023). Such concerns become particularly important in recruitment and other consequential HR processes, where employees expect decisions to remain transparent, accountable, reviewable, and subject to human oversight (Malin et al., 2025; Nawaz et al., 2024). Therefore, acceptance in traditional sectors may depend less on technological sophistication and more on perceived fairness, practical usefulness, transparency, and the preservation of meaningful human involvement.

Overall, digital maturity appears to influence the mechanisms through which employees evaluate AI-based HR applications. In technology-intensive sectors, frequent exposure to AI and stronger digital capabilities may increase the importance of perceived usefulness, ease of use, and trust. In traditional sectors, where AI is less embedded in daily work, acceptance may depend more strongly on organizational readiness, fairness, transparency, and concerns about the loss of human touch. This

sectoral distinction provides the basis for examining whether the determinants of AI acceptance vary systematically between technology-intensive and traditional industries.

Methodology

This study examines employee acceptance of AI-based human resources applications across six sectors. Table 1 presents the sector groupings and sample distribution, with 60 participants from each sector, 180 participants in each group and 360 participants in total. The grouping follows the distinction developed in the literature review between technology-oriented activities involving research and development, digital development and precision manufacturing, and established production, retail and hospitality activities in which operational and interpersonal work processes remain important. Technology-intensive and traditional are used as the study's sector groupings.

Table 1. Sector groupings and sample distribution

Sector group	Sector	Participants
Technology-intensive	Biotechnology	60
	Information technology	60
	Manufacture of computer, electronic and optical products	60
Traditional	Retail	60
	Textiles	60
	Hotels	60
Total		360

Participants were selected through purposive sampling. Eligibility criteria required participants to be at least 18 years old, actively employed in one of the relevant sectors, and sufficiently familiar with organizational human resources practices to evaluate AI-based HR applications. Participation in the study was voluntary.

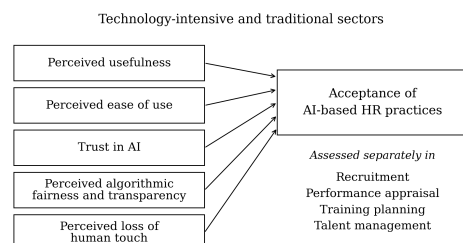


Figure 1. Conceptual research model of function-specific acceptance of AI-based HR practices.

Figure 1 presents the conceptual structure of the study by relating perceived usefulness, perceived ease of use, trust in AI, perceived algorithmic fairness and transparency, and perceived loss of human touch to AI acceptance in four HR functions. These relationships are considered separately for recruitment, performance appraisal, training planning, and talent management within technology-intensive and traditional sectors. In this way, the model provides a common framework for comparing the relationships between employee perceptions and AI acceptance across sector groups and HR functions.

Data Collection Tools

The study employed measurement instruments adapted from scales with established validity and reliability in the international literature. Each construct was assessed separately within four HR functions: recruitment, performance appraisal, training planning, and talent management. The measurement instruments, number of items, and original sources are presented in Table 2.

Table 2. Data collection tools

Construct	Validated Scale Used	Number of Items	Main Source
Acceptance of AI-Based HR Practices	Behavioral Intention Scale adapted from UTAUT/TAM and repeated separately for recruitment, performance appraisal, training planning, and talent management	12 items	Venkatesh et al. (2003); Davis (1989)
Perceived Usefulness	Perceived Usefulness Scale	6 items	Davis (1989)
Perceived Ease of Use	Perceived Ease of Use Scale	6 items	Davis (1989)
Trust in AI	Trust in Automation Scale	12 items	Jian et al. (2000)
Perceived AI-Algorithmic Fairness and Transparency	AIM-FAIR Scale	17 items	Ehrhardt et al. (2025)
Perceived Loss of Human Touch	Organizational Dehumanization Scale, adapted to AI-based HR context	8 items	Bell and Khoury (2011)

The statements in the scales were adapted separately for the four human resources functions to assess participants' tendencies to accept the use

of AI in each process. All scales used in the study were measured using a 5-point Likert-type rating scale (1 = Strongly Disagree, 5 = Strongly Agree).

Data Analysis Process

Data were analyzed using IBM SPSS Statistics 27. Descriptive statistics were calculated for participant characteristics and the research variables. Univariate normality was assessed through skewness and kurtosis values, which ranged from -0.74 to 0.81 and from -0.86 to 0.69, respectively. As these values remained within the recommended ± 3 range, no substantial departure from normality was observed, supporting the use of parametric analyses (Kline, 2023).

To evaluate the construct validity and reliability of the measurement instruments adapted to the AI-based HR context, Confirmatory Factor Analysis (CFA) was conducted using AMOS 27. The measurement model was specified as a pooled six-construct CFA model using functional item parcels (average item scores across the four HR functions per construct) as observed indicators. The maximum likelihood (ML) estimation method was employed. The overall model yielded an acceptable fit to the data: $\chi^2/df = 2.14$, CFI = .942, TLI = .935, and RMSEA = .056.

Convergent validity was established as item factor loadings exceeded .50 (ranging from .65 to .89), Composite Reliability (CR) values were well above the .70 threshold, and Average Variance Extracted (AVE) values exceeded the recommended .50 cutoff. The overall measurement model fit, construct validity, and composite reliability statistics are presented in Table 3.

Discriminant validity was assessed using both the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio of correlations. The HTMT ratios were computed using unadjusted directional correlation matrix outputs, wherein negative signs reflect inverse construct relationships (e.g., between Loss of Human Touch and AI Acceptance).

Table 3. Measurement Model, Construct Validity, and Reliability Analysis Results

Construct	Items	Factor Loadings (Range)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Acceptance of AI-Based HR Practices	12	0.71 - 0.88	0.952	0.618
Perceived Usefulness	6	0.68 - 0.84	0.895	0.588
Perceived Ease of Use	6	0.65 - 0.81	0.882	0.554
Trust in AI	12	0.73 - 0.89	0.950	0.625
Perceived Fairness and Transparency	17	0.70 - 0.86	0.962	0.602
Loss of Human Touch	8	0.66 - 0.82	0.912	0.567

Note: Factor loadings were obtained from the Overall Measurement Model (Pooled CFA) including all six constructs simultaneously. Overall Model Fit Indices: $\chi^2/df = 2.14$, CFI = .942, TLI = .935, and RMSEA = .056. All factor loadings are significant at $p < .001$.

As shown in Table 4, the square root of the AVE for each construct (displayed in bold along the diagonal) was greater than its highest correlation with any other construct, fulfilling the Fornell-Larcker condition. Furthermore, in all cases, the absolute HTMT values remained well below the conservative .85 cutoff threshold, confirming distinct empirical boundaries and discriminant validity between the constructs.

Table 4. Discriminant Validity Analysis Results (Fornell-Larcker Criterion and HTMT Ratio)

Construct	1	2	3	4	5	6
1. AI Acceptance	0.784	0.682	0.612	0.715	0.524	-0.412
2. Perceived Usefulness	0.612	0.767	0.589	0.645	0.481	-0.325
3. Perceived Ease of Use	0.541	0.512	0.744	0.598	0.412	-0.289
4. Trust in AI	0.634	0.578	0.531	0.799	0.495	-0.356
5. Fairness and Transparency	0.468	0.421	0.368	0.432	0.776	-0.487
6. Loss of Human Touch	-0.365	-0.288	-0.254	-0.312	-0.431	0.753

Note: Diagonal elements in bold text represent the square root of the Average Variance Extracted for each construct (Fornell-Larcker criterion). Values above the diagonal represent the Heterotrait-Monotrait ratio of correlations (HTMT < .85). Values below the diagonal represent bivariate Pearson correlation coefficients.

In addition to the overall measurement model validation, internal consistency across specific HR functions (recruitment, performance appraisal,

training planning and talent management) was further evaluated. As shown in Table 5, Cronbach's alpha coefficients ranged from .849 to .936 across all four functional domains, confirming high internal consistency for all measurement scales.

Table 5. Reliability Analysis Results Across HR Functions (Cronbach's Alpha)

	Recruitment	Performance appraisal	Training Planning	Talent Management
AI Acceptance	.894	.887	.913	.905
Perceived Usefulness	.876	.871	.889	.882
Perceived Ease of Use	.854	.849	.873	.867
Trust in AI	.912	.905	.924	.918
Perceived Fairness and Transparency	.931	.936	.928	.934
Loss of Human Touch	.863	.857	.852	.859

Analyses were conducted separately for technology-intensive and traditional sectors and for four HR functions: recruitment, performance appraisal, training planning, and talent management. Pearson correlation analyses were used to examine relationships among the research variables. Multiple linear regression analyses were then performed to assess the predictive roles of perceived usefulness, perceived ease of use, trust in AI, perceived fairness and transparency, and perceived loss of human touch in the acceptance of AI-based HR applications. The regression models were estimated separately for each sector group and HR function. To ensure that observed sectoral differences in AI acceptance were not confounded by demographic variations across sector groups hierarchical multiple regression analyses were performed as a robustness check. Demographic variables (age, education level, and work experience) were entered in Step 1, followed by the five main explanatory variables in Step 2. This two-stage procedure allowed for evaluating whether the predictive patterns of the core constructs remained stable after controlling for individual-level demographic characteristics.

To formally test whether the predictive relationships between explanatory variables and AI acceptance statistically differ across sector groups (rather than relying solely on separate subgroup regressions) interaction/moderation regression analyses were conducted.

To assess potential multicollinearity among the explanatory variables in the regression models, Variance Inflation Factor (VIF) and Tolerance statistics were calculated. Across all estimated models, VIF values remained well below the conservative cutoff threshold of 5.0, and Tolerance values were substantially above the minimum acceptable limit of 0.10. These diagnostics confirm that multicollinearity does not pose a threat to the stability or interpretation of the regression estimates.

Findings

Table 6. Demographic characteristics of the participants

Variable		Technology-Intensive (n = 180)	Traditional (n = 180)	Total (n = 360)
Gender	Female	53%	51%	52%
	Male	47%	49%	48%
Age	18-25	16%	11%	13%
	26-35	42%	36%	39%
	36-45	26%	29%	27%
	46-55	12%	17%	15%
	56 +	4%	7%	6%
Education	High School	11%	23%	17%
	Bachelor	57%	56%	57%
	Masters /PhD	32%	21%	26%
Work Experience	Less than 5 years	39%	27%	33%
	5-10 years	33%	36%	35%
	11-15 years	18%	22%	20%
	15 years +	10%	15%	12%

As shown in Table 6, the sample consisted of equal numbers of employees from technology-intensive and traditional sectors. Gender distribution was also broadly balanced across the two sector groups. Participants in technology-intensive sectors were relatively younger and more highly educated, whereas traditional sectors included a higher proportion of employees with longer work experience and high school-level education.

Table 7. Descriptive statistics of research variables

Variable	Sector	Statistic	Recruitment	Performance Appraisal	Training Planning	Talent Management
AI Acceptance	Technology-Intensive	Mean	3.62	3.55	4.12	4.06
		Std. dev.	0.74	0.77	0.63	0.65
	Traditional	Mean	3.48	3.42	3.96	3.88
		Std. dev.	0.81	0.84	0.71	0.73
Perceived Usefulness	Technology-Intensive	Mean	4.18	4.10	4.36	4.29
		Std. dev.	0.61	0.65	0.56	0.59
	Traditional	Mean	3.82	3.76	4.08	3.98
		Std. dev.	0.71	0.73	0.65	0.68
Perceived Ease of Use	Technology-Intensive	Mean	4.09	4.04	4.58	4.61
		Std. dev.	0.64	0.66	0.58	0.61
	Traditional	Mean	3.79	3.74	4.01	3.92
		Std. dev.	0.72	0.74	0.61	0.63
Trust in AI	Technology-Intensive	Mean	4.15	4.08	4.29	4.21
		Std. dev.	0.60	0.63	0.55	0.58
	Traditional	Mean	3.77	3.71	4.02	3.95
		Std. dev.	0.74	0.75	0.62	0.65
Perceived Fairness and Transparency	Technology-Intensive	Mean	3.74	3.69	3.80	3.77
		Std. dev.	0.70	0.73	0.68	0.69
	Traditional	Mean	4.12	4.18	4.08	4.15
		Std. dev.	0.63	0.61	0.68	0.69
Loss of Human Touch	Technology-Intensive	Mean	2.84	2.92	2.71	2.76
		Std. dev.	0.82	0.79	0.85	0.83
	Traditional	Mean	3.62	3.74	3.48	3.56
		Std. dev.	0.74	0.71	0.77	0.78

Table 7 presents the descriptive statistics for the research variables. Technology-intensive sectors showed descriptively higher mean scores for AI acceptance, perceived usefulness, perceived ease of use, and trust in AI across all four HR functions. In contrast, perceived fairness and transparency and perceived loss of human touch were higher in traditional sectors. In both sector groups, AI acceptance was higher for training planning and talent management than for recruitment and performance appraisal.

Table 8. Pearson correlation analysis results / Technology-intensive sectors

		AI Acceptance (Recruitment)	AI Acceptance (Performance Appraisal)	AI Acceptance (Training Planning)	AI Acceptance (Talent Management)
Perceived Usefulness (PU)	r	.612**	.521**	.621**	.545**
	p	.001	.003	<.001	<.001
Perceived Ease of Use (PEOU)	r	.541**	.468**	.654**	.488**
	p	.003	.009	.001	<.001
Trust in AI	r	.587**	.502**	.689**	.512**
	p	.002	.005	<.001	<.001
Perceived Fairness and Transparency	r	.398**	.421**	.412**	.436**
	p	.003	.002	.002	.001
Loss of Human Touch	r	-.298**	-.365**	-.241	-.265
	p	<.001	.004	.198	.158

**p < .01; *p < .05

Pearson correlation analyses were subse-

quently conducted separately for technology-intensive and traditional sectors to examine the relationships between AI acceptance and the explanatory variables across the four HR functions.

As shown in Table 8, perceived usefulness, perceived ease of use, trust in AI, and perceived fairness and transparency were positively associated with AI acceptance across all four HR functions in technology-intensive sectors. The strongest relationship was observed between trust in AI and acceptance in training planning ($r = .689$, $p < .001$). Perceived loss of human touch showed significant negative correlations with AI acceptance in recruitment ($r = -.298$, $p < .001$) and performance appraisal ($r = -.365$, $p = .004$). Its correlations with acceptance in training planning and talent management were not statistically significant.

Table 9. Pearson correlation analysis results / Traditional sectors

		AI Acceptance (Recruitment)	AI Acceptance (Performance Appraisal)	AI Acceptance (Training Planning)	AI Acceptance (Talent Management)
Perceived Usefulness (PU)	r	.332**	.298	.512**	.612**
	p	.004	.090	.004	.001
Perceived Ease of Use (PEOU)	r	.298	.276	.468**	.564**
	p	.090	.118	.009	.002
Trust in AI	r	.315	.312	.501**	.598**
	p	.082	.084	.005	.001
Perceived Fairness and Transparency	r	.598**	.612**	.598**	.654**
	p	.001	.001	.001	<.001
Loss of Human Touch	r	-.487**	-.521**	-.312**	-.365**
	p	.006	.003	.004	.003

**p < .01; *p < .05

As shown in Table 9, AI acceptance in recruitment was positively associated with perceived usefulness and perceived fairness and transparency, and negatively associated with perceived loss of human touch. Perceived ease of use and trust in AI were not significantly related to recruitment acceptance. In performance appraisal, perceived fairness and transparency showed a positive relationship, whereas perceived loss of human touch showed a negative relationship; the remaining variables were not statistically significant. In training planning and talent management, perceived usefulness, perceived ease of use, trust in AI, and perceived fairness and transparency were

positively associated with AI acceptance, while perceived loss of human touch was negatively associated with acceptance.

Following the correlation analyses, multiple linear regression analyses were conducted separately for technology-intensive and traditional sectors to examine the predictors of AI acceptance across recruitment, performance appraisal, training planning, and talent management. Prior to evaluating the regression models, multicollinearity diagnostics were systematically examined to ensure that inter-correlations among the explanatory variables did not distort parameter estimations. Across all estimated models, Tolerance values were well above the acceptable threshold of .10, and Variance Inflation Factor (VIF) values remained comfortably below the conservative cutoff limit of 5.0, confirming the absence of severe multicollinearity and supporting the stability of the estimated coefficients.

Table 10. Multiple regression analysis results for AI acceptance in recruitment

Sector	Independent variable	Dependent variable	Model R ²	β	Sig (p)	Tol.	VIF
Technology-Intensive	PU →	AI Acceptance in Recruitment	0.61	.365	.005**	.54	1.85
	PEOU →			.271	.022*	.61	1.64
	Trust in AI →			.318	.009**	.58	1.72
	Perceived Fairness and Transparency →			.182	.095	.68	1.47
	Loss of Human Touch →			-.112	.244	.78	1.28
Traditional	PU →	AI Acceptance in Recruitment	0.67	.212	.084	.52	1.92
	PEOU →			.158	.149	.59	1.69
	Trust in AI →			.191	.096	.55	1.82
	Perceived Fairness and Transparency →			.401	.002**	.64	1.56
	Loss of Human Touch →			-.312	.005**	.72	1.39

PU=Perceived Usefulness; PEOU=Perceived Ease of Use; Tol.=Tolerance; VIF=Variance Inflation Factor **p < .01; *p < .05

As shown in Table 10, perceived usefulness, perceived ease of use, and trust in AI were significant positive predictors of recruitment-related AI acceptance in technology-intensive sectors, whereas perceived fairness and transparency and loss of human touch were not significant. The model explained 61% of the variance in AI acceptance. In traditional sectors, perceived fairness and transparency positively predicted AI acceptance, while loss of human touch had a signifi-

cant negative predictive role. Perceived usefulness, perceived ease of use, and trust in AI were not significant predictors, and the model explained 67% of the variance.

Table 11. Multiple regression analysis results for AI acceptance in performance appraisal

Sector	Independent variable	Dependent variable	Model R ²	β	Sig (p)	Tol.	VIF
Technology-Intensive	PU →	AI Acceptance in Performance Appraisal	0.59	.321	.011*	.56	1.79
	PEOU →			.268	.025*	.63	1.59
	Trust in AI →			.292	.016*	.59	1.69
	Perceived Fairness and Transparency →			.214	.059	.66	1.52
	Loss of Human Touch →			-.221	.044*	.75	1.33
Traditional	PU →	AI Acceptance in Performance Appraisal	0.66	.185	.142	.54	1.85
	PEOU →			.158	.152	.60	1.67
	Trust in AI →			.201	.094	.57	1.75
	Perceived Fairness and Transparency →			.418	.001**	.62	1.61
	Loss of Human Touch →			-.336	.003**	.70	1.43

PU=Perceived Usefulness; PEOU=Perceived Ease of Use; Tol.=Tolerance; VIF=Variance Inflation Factor **p < .01; *p < .05

As shown in Table 11, perceived usefulness, perceived ease of use, and trust in AI positively predicted AI acceptance in performance appraisal within technology-intensive sectors, whereas perceived loss of human touch had a significant negative predictive role. Perceived fairness and transparency was not a significant predictor, and the model explained 59% of the variance. In traditional sectors, perceived fairness and transparency positively predicted AI acceptance, while perceived loss of human touch negatively predicted acceptance. Perceived usefulness, perceived ease of use, and trust in AI were not significant predictors, and the model explained 66% of the variance.

Table 12. Multiple regression analysis results for AI acceptance in training planning

Sector	Independent variable	Dependent variable	Model R ²	β	Sig (p)	Tol.	VIF
Technology-Intensive	PU →	AI Acceptance in Training Planning	0.53	.445	<.001**	.48	2.08
	PEOU →			.362	.001**	.52	1.92
	Trust in AI →			.401	.001**	.46	2.17
	Perceived Fairness and Transparency →			.168	.091	.64	1.56
	Loss of Human Touch →			-.112	.203	.79	1.27
Traditional	PU →	AI Acceptance in Training Planning	0.58	.298	.011*	.55	1.82
	PEOU →			.268	.017*	.61	1.64
	Trust in AI →			.281	.014*	.58	1.72
	Perceived Fairness and Transparency →			.341	.005**	.65	1.54
	Loss of Human Touch →			-.224	.031*	.74	1.35

PU=Perceived Usefulness; PEOU=Perceived Ease of Use; Tol.=Tolerance; VIF=Variance Inflation Factor **p < .01; *p < .05

As shown in Table 12, perceived usefulness, perceived ease of use, and trust in AI positively predicted AI acceptance in training planning within technology-intensive sectors, whereas perceived fairness and transparency and perceived loss of human touch were not significant predictors. The model explained 53% of the variance. In traditional sectors, perceived usefulness, perceived ease of use, trust in AI, and perceived fairness and transparency positively predicted AI acceptance, while perceived loss of human touch had a significant negative predictive role. The model explained 58% of the variance.

Table 13. Multiple regression analysis results for AI acceptance in talent management

Sector	Independent variable	Dependent variable	Model R ²	β	Sig (p)	Tol.	VIF
Technology-Intensive	PU	→	0.57	.336	.006**	.52	1.92
	PEOU	→		.271	.018*	.59	1.69
	Trust in AI	→		.298	.011*	.55	1.82
	Perceived Fairness and Transparency	→		.176	.083	.65	1.54
	Loss of Human Touch	→		-.109	.231	.77	1.30
Traditional	PU	→	0.64	.264	.024*	.50	2.00
	PEOU	→		.241	.031*	.57	1.75
	Trust in AI	→		.258	.028*	.53	1.89
	Perceived Fairness and Transparency	→		.372	.002**	.60	1.67
	Loss of Human Touch	→		-.228	.039*	.72	1.39

PU=Perceived Usefulness; PEOU=Perceived Ease of Use; Tol.=Tolerance; VIF=Variance Inflation Factor **p < .01; *p < .05

As shown in Table 13, perceived usefulness, perceived ease of use, and trust in AI positively predicted AI acceptance in talent management within technology-intensive sectors, whereas perceived fairness and transparency and perceived loss of human touch were not significant predictors. The model explained 57% of the variance. In traditional sectors, perceived usefulness, perceived ease of use, trust in AI, and perceived fairness and transparency positively predicted AI acceptance, while perceived loss of human touch had a significant negative predictive role. The model explained 64% of the variance.

To address potential confounding effects resulting from demographic discrepancies between technology-intensive and traditional sector samples (e.g., younger and more educated participants

in technology-intensive sectors versus more experienced participants in traditional sectors), hierarchical regression models were estimated across all four HR functions. In Step 1, Age, Education Level, and Work Experience were entered as control variables. In Step 2, Perceived Usefulness, Perceived Ease of Use, Trust in AI, Perceived Algorithmic Fairness and Transparency, and Perceived Loss of Human Touch were added to the model.

Table 14. Hierarchical regression analysis results controlling for demographic variables (Robustness Check)

HR Function & Sector Group	Step 1: Control Variables (R ²)	Step 2: Main Predictors Added (R ²)	ΔR^2	Significant Predictors in Step 2 (p)	Sig. (p)
Recruitment					
Technology-Intensive	.03	.62	.59***	PU (.358**), PEOU (.264*), Trust (.310**)	<.001
Traditional	.04	.68	.64***	Fairness (.392**), Loss of Human Touch (-.305**)	<.001
Performance Appraisal					
Technology-Intensive	.02	.60	.58***	PU (.315*), PEOU (.260*), Trust (.285*), Loss of HT (-.212*)	<.001
Traditional	.05	.67	.62***	Fairness (.410**), Loss of Human Touch (-.328**)	<.001
Training Planning					
Technology-Intensive	.03	.54	.51***	PU (.438**), PEOU (.355**), Trust (.392**)	<.001
Traditional	.04	.59	.55***	PU (.290*), PEOU (.261*), Trust (.275*), Fairness (.332**), Loss of HT (-.218*)	<.001
Talent Management					
Technology-Intensive	.02	.58	.56***	PU (.330**), PEOU (.265*), Trust (.291*)	<.001
Traditional	.03	.65	.62***	PU (.258*), PEOU (.235*), Trust (.250*), Fairness (.365**), Loss of HT (-.220*)	<.001

Note: Step 1 controls: Age (1=18-25; 2=26-35; 3=36-45; 4=46-55; 5=56+), Education Level (1=High School; 2=Bachelor; 3=Master/PhD), Work Experience (1=<5 yrs; 2=5-10 yrs; 3=11-15 yrs; 4=15+ yrs). PU = Perceived Usefulness, PEOU = Perceived Ease of Use, Trust = Trust in AI, Fairness = Perceived Algorithmic Fairness and Transparency, Loss of HT = Perceived Loss of Human Touch. ***p < .001.

As summarized in Table 14, the inclusion of demographic control variables in Step 1 explained a minimal proportion of variance (R² ranging from .02 to .05 across models, p > .05). When the main explanatory variables were introduced in Step 2, the models produced statistically significant variance

changes (ΔR^2 ranging from .51 to .64, $p < .001$). Crucially, the regression coefficients (β), directionality, and significance levels of the primary independent variables remained consistent with the unadjusted models reported in Tables 10-13. These results show that the subgroup predictive patterns remain stable after controlling for age, education level, and work experience. The interaction models in Table 15 identify the specific relationships that differ significantly between sector groups.

To assess whether the predictive coefficients of the main explanatory variables statistically differ between technology-intensive and traditional sectors, moderation models were tested by including interaction terms. As shown in Table 15, five interaction terms were statistically significant, identifying specific differences in predictive relationships between the two sector groups.

Table 15. Moderation regression analysis results testing cross-sectoral interaction effects (Predictor $\times$ Sector Group)

HR Function & Independent Variable	Main Effect (β)	Sector Dummy (β)	Interaction Term (Predictor $\times$ Sector) (β)	Sig. (p)	Structural Moderation Decision
Recruitment					
Perceived Usefulness	.212	.142	.153	.112	Not Significant
Perceived Ease of Use	.158	.142	.113	.210	Not Significant
Trust in AI	.191	.142	.127	.168	Not Significant
Perceived Fairness and Transparency	.401**	.142	-.242**	.003	Significant (Stronger in Traditional)
Loss of Human Touch	-.312**	.142	.201*	.014	Significant (Stronger in Traditional)
Performance Appraisal					
Perceived Usefulness	.185	.128	.136	.145	Not Significant
Perceived Ease of Use	.158	.128	.110	.224	Not Significant
Trust in AI	.201	.128	.091	.312	Not Significant
Perceived Fairness and Transparency	.418**	.128	-.218**	.008	Significant (Stronger in Traditional)
Loss of Human Touch	-.336**	.128	.115	.182	Not Significant
Training Planning					
Perceived Usefulness	.298*	.115	.147	.102	Not Significant
Perceived Ease of Use	.268*	.115	.094	.280	Not Significant
Trust in AI	.281*	.115	.215*	.011	Significant (Stronger in Tech-Intensive)

HR Function & Independent Variable	Main Effect (β)	Sector Dummy (β)	Interaction Term (Predictor $\times$ Sector) (β)	Sig. (p)	Structural Moderation Decision
Perceived Fairness and Transparency	.341**	.115	-.173	.071	Not Significant
Loss of Human Touch	-.224*	.115	.112	.215	Not Significant
Talent Management					
Perceived Usefulness	.264*	.121	.189*	.024	Significant (Stronger in Tech-Intensive)
Perceived Ease of Use	.241*	.121	.030	.721	Not Significant
Trust in AI	.258*	.121	.040	.632	Not Significant
Perceived Fairness and Transparency	.372**	.121	-.196	.052	Not Significant
Loss of Human Touch	-.228*	.121	.119	.190	Not Significant

Note: Sector Group reference category: 0 = Traditional Sectors, 1 = Technology-Intensive Sectors. Controlled for Age, Education Level, and Work Experience. ** $p < .01$, * $p < .05$.

For recruitment and performance appraisal, the interaction terms for Perceived Algorithmic Fairness and Transparency were negative and statistically significant ($\beta = -.242$, $p = .003$ and $\beta = -.218$, $p = .008$, respectively). These results show that the positive association of perceived fairness and transparency with AI acceptance was stronger in traditional sectors than in technology-intensive sectors for these two functions. The interaction term for Perceived Loss of Human Touch in recruitment was positive and statistically significant ($\beta = .201$, $p = .014$), indicating that its negative association with AI acceptance was stronger in traditional sectors.

For training planning, the interaction term for Trust in AI was positive and statistically significant ($\beta = .215$, $p = .011$), showing a stronger positive association with AI acceptance in technology-intensive sectors. For talent management, the interaction term for Perceived Usefulness was positive and statistically significant ($\beta = .189$, $p = .024$), showing a stronger positive association in technology-intensive sectors. Together with the recruitment and performance appraisal findings, these five significant interactions identify the specific relationships moderated by sector group. The remaining interaction terms were not statistically significant.

Discussion and Conclusion

This study demonstrates that employee acceptance of AI-based human resources applications varies according to both sectoral context and the HR function in which AI is used. In the subgroup regressions for technology-intensive sectors, perceived usefulness, perceived ease of use, and trust in AI emerged as significant positive predictors of acceptance across the four HR functions. This finding supports the continued relevance of the Technology Acceptance Model and UTAUT in digitally mature organizational settings (Davis, 1989; Venkatesh et al., 2003). Employees in these sectors appear to perceive AI-based HR applications as extensions of existing digital workflows rather than as unfamiliar technologies. The interaction findings further show that the positive association of trust in AI with acceptance in training planning and that of perceived usefulness in talent management are stronger in technology-intensive sectors.

In the subgroup regressions for traditional sectors, perceived fairness and transparency positively predicted acceptance, while perceived loss of human touch negatively predicted acceptance across the four HR functions. The interaction findings show that the positive association of fairness and transparency is stronger in traditional sectors for recruitment and performance appraisal, while the negative association of loss of human touch is stronger in traditional sectors for recruitment. These findings suggest that employees in traditional sectors evaluate AI-based HR applications through ethical and normative considerations in addition to their technical utility. Employees appear to be concerned with whether algorithmic decisions are understandable, reviewable, fair, and subject to human oversight. This result is consistent with research emphasizing algorithmic justice, ethical legitimacy, accountability, and employee reactions as central conditions of AI acceptance in HRM (Bujold et al., 2024; Golgeci et al., 2025; Köchling & Wehner, 2020).

Sectoral differences may reflect variations in digital maturity, workforce capabilities, and the or-

ganization of work. Employees in technology-intensive sectors are generally more familiar with data-driven tools, automation, and digital decision-support systems. Their evaluations of AI therefore tend to focus on functionality, usability, and trust. In traditional sectors, where work processes may depend more strongly on face-to-face interaction, practical experience, physical operations, and direct supervision, AI-based HR systems may represent a more substantial organizational change. The stronger associations of fairness and transparency in recruitment and performance appraisal, together with loss of human touch in recruitment, give these considerations particular relevance in traditional sectors.

The findings also indicate that AI acceptance should not be treated as a uniform attitude across HR functions. Training planning and talent management generally received higher acceptance than recruitment and performance appraisal. Employees may regard AI more positively when it supports learning, development, career planning, and talent matching. Recruitment and performance appraisal, in contrast, involve consequential judgments concerning employment, career opportunities, performance, and organizational justice. These functions therefore generate stronger expectations regarding explainability, procedural fairness, and human review.

The negative predictive role of perceived loss of human touch in performance appraisal within technology-intensive sectors is particularly noteworthy. Perceived loss of human touch also showed a significant negative correlation with recruitment acceptance in these sectors. These findings highlight the importance of human involvement in recruitment and performance appraisal in digitally mature settings. Even in digitally mature settings, employees may expect performance judgments to incorporate contextual knowledge, managerial interpretation, and opportunities for dialogue. Human oversight therefore remains important when AI-generated assessments directly affect professional identity, autonomy, and career outcomes.

The findings have important practical implications. Organizations should avoid applying a uniform AI implementation strategy across sectors and HR functions. The positive subgroup associations of perceived usefulness, perceived ease of use, and trust in AI support attention to usefulness, usability, and reliability when introducing AI. The interaction findings identify more specific priorities for each sector group. In technology-intensive sectors, building trust is particularly relevant to training planning, while demonstrating usefulness is particularly relevant to talent management. In traditional sectors, fairness and transparency deserve particular attention in recruitment and performance appraisal, with preservation of human involvement also particularly relevant to recruitment. In high-stakes processes such as recruitment and performance appraisal, positioning AI as a decision-support mechanism rather than an autonomous decision-maker may be particularly important.

In conclusion, the successful implementation of AI-based HR practices depends on more than technical integration. The subgroup findings show the relevance of conventional technology acceptance variables alongside fairness, transparency, and human involvement. Five significant interactions specify how these relationships differ between sector groups. Fairness and transparency have stronger positive associations with acceptance in traditional sectors for recruitment and performance appraisal, while loss of human touch has a stronger negative association for recruitment. Trust in AI in training planning and perceived usefulness in talent management have stronger positive associations in technology-intensive sectors. These findings support consideration of the particular HR function when interpreting sectoral differences in AI acceptance.

Limitations and Future Research

The study is limited to six sectors and employee perceptions measured within four HR functions. Participants were selected through purposive sampling, which limits the generalizability of the

findings to the wider employee population. Equal numbers of participants from each sector support a balanced sample structure, but the findings should be considered in relation to the employees and sectors included in the study. In addition, the measured perceptions provide information about how employees evaluate AI-based HR practices. Further research could examine how these evaluations relate to actual use of AI systems and experiences with their implementation.

With respect to the interpretation of sectoral variation, institutional arrangements, organizational conditions, labor-market characteristics, and the national context may also influence employee acceptance. These factors were not included among the explanatory variables examined in the study. Regulatory expectations and employee representation may shape perceptions of fairness and accountability, while organizational size, management practices, digital infrastructure, and opportunities for training may affect employees' familiarity with AI. Labor-market conditions, occupational differences, and concerns about employment security may also contribute to the meaning employees assign to AI-based HR practices. For this reason, the sector grouping should be considered alongside differences within sectors and the conditions under which organizations introduce AI.

Future research may extend these findings by examining different national contexts, organizational sizes, occupational groups, and forms of AI-supported decision-making. Qualitative interviews could provide a more detailed understanding of how employees interpret usefulness, fairness, trust, and the preservation of human involvement in particular HR processes. Mixed-methods designs could combine these accounts with survey findings to explain the conditions associated with acceptance across sectors. Longitudinal designs could examine how employee perceptions and acceptance develop as experience with AI-based HR practices increases and organizational arrangements change.

Declarations

Funding: The author received no financial support for the research, authorship, and / or publication of this article.

Conflicts of Interest: The author declares no conflicts of interest related to this study.

Declaration of Previous Presentation and Publication: An earlier version of this manuscript was presented at XI. International Academic Studies Congress on April 28, 2026. This manuscript has not been previously published in any journal or book.

Ethical Approval: Ethical committee approval for this study was obtained from Social and Human Sciences Research Ethics Committee of Istanbul Kent University on April 10, 2026 (decision/document number: 2026/04).

Informed Consent: Written informed consent was obtained from all participants included in the study (Adult employees (18 years and older) working in technology-intensive and traditional industries).

Data Availability: The data are not publicly available due to the data cannot be made publicly available due to ethical and confidentiality restrictions outlined in the research protocol. The study's confidentiality commitments require that participant-level data remain accessible only to the authorized researchers. Accordingly, the dataset is securely stored and cannot be shared with third parties.

AI Disclosure: ChatGPT was used for language editing, grammar checking and formatting support. The author reviewed, edited, and verified all AI-assisted outputs and takes full responsibility for the content of the manuscript.

References

Ali, A., Cichon, D., & Abbas, A. (2026). AI-driven HRM digitization in effect: Mechanisms, conditions,

and employee outcomes. *Journal of Innovation & Knowledge*, 13, Article 100919. <https://doi.org/10.1016/j.jik.2025.100919>

Bell, C.M. & Khoury, C. (2011). Organizational De/Humanization, Deindividuation, Anomie, and in/Justice. In S.W. Gilliland, D.D. Steiner & D. P. Skarlicki (Eds.). *Emerging Perspectives on Organizational Justice and Ethics* (pp. 167-197). Charlotte: IAP Information Age Publishing. <https://doi.org/10.1108/978-1-61735-583-720251010>

Bertola, P., & Teunissen, J. (2018). Fashion 4.0: Innovating the fashion industry through digital transformation. *Research Journal of Textile and Apparel*, 22(4), 352-369. <https://doi.org/10.1108/RJTA-03-2018-0023>

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization*, 24(2), 239-257. <https://doi.org/10.1017/jmo.2016.55>

Bujold, A., Roberge-Maltais, I., Parent-Rochelleau, X., Boasen, J., Sénécal, S., & Léger, P.-M. (2024). Responsible artificial intelligence in human resources management: A review of the empirical literature. *AI and Ethics*, 4, 1185-1200. <https://doi.org/10.1007/s43681-023-00325-1>

Calvino, F., Dernis, H., Samek, L., & Ughi, A. (2024). A sectoral taxonomy of AI intensity. OECD Artificial Intelligence Papers, No. 30. OECD Publishing. <https://doi.org/10.1787/1f6377b5-en>

Chen, X., Ke, J., Zhang, X., & Chen, J. (2025). The impact of AI anxiety on employees' work passion: A moderated mediated effect model. *Acta Psychologica*, 260, 105487. <https://doi.org/10.1016/j.actpsy.2025.105487>

Choung, H., David, P., & Ross, A. (2023). Trust in AI and its role in the acceptance of AI technologies. *International Journal of Human-Computer Interaction*, 39(9), 1727-1739. <https://doi.org/10.1080/10447318.2022.2050543>

CIPD. (2025). Almost two-thirds of people trust AI to inform important work decisions. <https://www.cipd.org/en/about/press-releases/almost-two-thirds-people-trust-ai-to-inform-important-work-decisions/>

- Collings, D. G., & Mellahi, K. (2009). Strategic talent management: A review and research agenda. *Human Resource Management Review*, 19(4), 304-313. <https://doi.org/10.1016/j.hrmr.2009.04.001>
- Dadaboyev, S.M.U., Abdullayeva, J., Abbosova, N., et al. (2025). Role of artificial intelligence in employee recruitment: systematic review and future research directions. *Discover Global Society*, 3, 99. <https://doi.org/10.1007/s44282-025-00246-w>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340. <https://doi.org/10.2307/249008>
- Ehrhardt, N., Renn, M. & Utz, S. (2025). Navigating fairness: introducing the multidimensional AIM-FAIR scale for evaluating AI decision-making. *AI & Society*, 40, 6181-6199. <https://doi.org/10.1007/s00146-025-02354-2>
- Eurostat. (2026). *Use of artificial intelligence in enterprises*. Statistics Explained.
- Gillespie, N., Lockey, S., Ward, T., Macdade, A., & Hassed, G. (2025). Trust, attitudes, and use of artificial intelligence: A global study 2025. The University of Melbourne & KPMG. <https://doi.org/10.26188/28822919>
- Golgeci, I., Ritala, P., Arslan, A., McKenna, B., & Ali, I. (2025). Confronting and alleviating AI resistance in the workplace: An integrative review and a process framework. *Human Resource Management Review*, 35(2), 101075. <https://doi.org/10.1016/j.hrmr.2024.101075>
- Gong, Q., Fan, D., & Bartram, T. (2025). Integrating artificial intelligence and human resource management: A review and future research agenda. *The International Journal of Human Resource Management*, 36(1), 103-141. <https://doi.org/10.1080/09585192.2024.2440065>
- Horodyski, P. (2023). Applicants' perception of artificial intelligence in the recruitment process. *Computers in Human Behavior Reports*, 11, 100303. <https://doi.org/10.1016/j.chbr.2023.100303>
- Jian, J.-Y., Bisantz, A.M. & Drury, C.G. (2000). Foundations for an Empirically Determined Scale of Trust in Automated Systems. *International Journal of Cognitive Ergonomics*, 4(1), 53-71. <https://doi.org/10.1207/S15327566IJCE040104>
- Kergroach, S., & Heritier, J. (2025). Emerging divides in the transition to artificial intelligence. *OECD Regional Development Papers*, 147. OECD Publishing. <https://doi.org/10.1787/7376c776-en>
- Kline, R.B. (2023). *Principles and Practice of Structural Equation Modeling*. 5th Ed. Guilford Press.
- Köchling, A., & Wehner, M. C. (2020). Discriminated by an algorithm: A systematic review of discrimination and fairness in algorithmic decision-making in the context of HR recruitment and HR development. *Business Research*, 13, 795-848. <https://doi.org/10.1007/s40685-020-00134-w>
- Lewis, R. E., & Heckman, R. J. (2006). Talent management: A critical review. *Human Resource Management Review*, 16(2), 139-154. <https://doi.org/10.1016/j.hrmr.2006.03.001>
- Malin, C., Fleiß, J., & Thalmann, S. (2025). Stakeholder-specific adoption of AI in HRM: Workers' representatives' perspective on concerns, requirements, and measures. *Frontiers in Artificial Intelligence*, 8, 1561322. <https://doi.org/10.3389/frai.2025.1561322>
- Mittal, S., Khan, M. A., Romero, D., & Wuest, T. (2018). A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises. *Journal of Manufacturing Systems*, 49, 194-214. <https://doi.org/10.1016/j.jmsy.2018.10.005>
- Moeuf, A., Pellerin, R., Lamouri, S., Tamayo-Giraldo, S., & Barbaray, R. (2018). The industrial management of SMEs in the era of Industry 4.0. *International Journal of Production Research*, 56(3), 1118-1136. <https://doi.org/10.1080/00207543.2017.1372647>
- Naim, I., Tanveer, M. I., Gildea, D., & Hoque, M. E. (2015). Automated analysis and prediction of job interview performance. *Human-Computer Interaction*. <https://arxiv.org/abs/1504.03425>
- Nawaz, N., Arunachalam, H., Pathi, B. K., & Gajenderan, V. (2024). The adoption of artificial intelligence

- in human resources management practices. *International Journal of Information Management Data Insights*, 4(1), 100208.
<https://doi.org/10.1016/j.jiimei.2023.100208>
- Nguyen, P., Watson, G. P., Barnes, D., Agrawal, S., Schuster, A. M., & Cotten, S. R. (2026). Navigating workplace AI adoption: The influence of perceptions and affective attitudes on employees' intentions to use AI at work. *Journal of Management & Organization*, 32(4), 1018-1043. <https://doi.org/10.1017/jmo.2026.10090>
- OECD. (2024). *Using AI in the workplace: Opportunities, risks, and policy responses*. OECD Publishing.
- OECD. (2026). *AI and skills*. OECD Publishing.
- Rauhala, M., Drake, M., & Saaranen, P. (2026). Ethical AI in the workplace: Ensuring fairness and transparency. *AI and Ethics*, 6, 12.
<https://doi.org/10.1007/s43681-025-00903-5>
- Rigotti, C., & Fosch-Villaronga, E. (2024). Fairness, AI, and recruitment. *Computer Law & Security Review*, 53, 105966.
<https://doi.org/10.1016/j.clsr.2024.105966>
- Savolainen, I., Ylinen, L., Grönroos, R., & Oksanen, A. (2026). AI transformation in working life: A systematic review of usage and attitudes toward AI among workers. *Digital Business*, 6(1), 100162. <https://doi.org/10.1016/j.dig-bus.2025.100162>
- Seo, K. H., & Lee, J. H. (2021). The emergence of service robots at restaurants: Integrating trust, perceived risk, and satisfaction. *Sustainability*, 13(8), Article 4431.
<https://doi.org/10.3390/su13084431>
- Tusquellas, N., Palau, R., & Santiago, R. (2024). Analysis of the potential of artificial intelligence for professional development and talent management: A systematic literature review. *International Journal of Information Management Data Insights*, 4(2), Article 100288.
<https://doi.org/10.1016/j.jiimei.2024.100288>
- Ubeda-Garcia, M., Marco-Lajara, B., Zaragoza-Saez, P. C., & Poveda-Pareja, E. (2025). Artificial intelligence, knowledge, and human resource management: A systematic literature review of theoretical tensions and strategic implications. *Journal of Innovation & Knowledge*, 10(6), 100809.
<https://doi.org/10.1016/j.jik.2025.100809>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478.
<https://doi.org/10.2307/30036540>
- Yıldız, F. Z. (2025). İnsan kaynakları yönetiminde yapay zekâ: uygulamalar ve gelecek yönelimleri üzerine kapsamlı bir çalışma. *Yönetim Bilimleri Dergisi*, 23(57), 1569-1594.
<https://doi.org/10.35408/comuybd.1569970>
- Yu, L., & Li, Y. (2022). Artificial intelligence decision-making transparency and employees' trust: The parallel multiple mediating effect of effectiveness and discomfort. *Behavioral Sciences*, 12(5), 127.
<https://doi.org/10.3390/bs12050127>