

Artificial Intelligence Adoption in Human Resource Management: Implications for Staff Efficiency, Workload Management, and Employee Performance

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Abstract

The rapid integration of Artificial Intelligence (AI) into human resource management (HRM) practices is reshaping organizational operations, with significant implications for employee performance and workplace experience. Grounded in the Job Demands–Resources (JD–R) model and socio-technical systems theory, this study examines the influence of AI adoption on staff efficiency, workload reduction, and employee performance, while assessing the moderating effects of job satisfaction and job security. Existing literature highlights AI's capacity to streamline administrative processes, optimize decision-making, and enhance HR service delivery; however, concerns related to technological replacement and employee morale remain central challenges in AI-enabled workplaces. A quantitative research design was employed, utilizing survey data collected from 395 employees across diverse organizational settings. Rigorous data screening ensured the reliability of the dataset, followed by comprehensive analyses including reliability assessments, convergent and discriminant validity, descriptive statistics, correlation tests, and regression-based moderation models. The findings reveal that AI adoption significantly improves staff efficiency and reduces workload, which subsequently enhances employee performance. Moreover, job satisfaction positively moderates the relationship between AI adoption and performance, indicating that satisfied employees are more inclined to embrace AI tools. Job security also emerges as a critical moderator, reducing fears of technological displacement and promoting constructive engagement with AI systems. The study concludes that AI adoption in HRM can substantially improve performance outcomes, but its success depends on simultaneously addressing employees' psychological needs. These findings contribute to organizational sustainability by supporting the UN Sustainable Development Goals (SDG 8: Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure), emphasizing the need for balanced technological innovation that safeguards employee well-being. Practical implications highlight the necessity of employee-centered policies to ensure sustainable AI implementation..

Keywords: Human resource management; Employee performance; Job satisfaction; Job security; Workload reduction; Staff efficiency; Socio-technical systems.

Introduction

The rapid integration of Artificial Intelligence (AI) into organizational systems has created both opportunities and challenges for human resource management (HRM). While AI promises enhanced efficiency, reduced administrative burden, and improved decision-making, its adoption also raises complex human, organizational, and psychological concerns that remain insufficiently explored. The core problem is that the introduction of AI into HRM practices has outpaced empirical understanding of how it influences employees' performance, perceptions, and workplace experiences. Existing research often highlights the technological advantages of AI, yet comparatively little is known about the nuanced human reactions that ultimately determine whether AI systems succeed or fail in practice (Jarrahi, 2018; Meijerink et al., 2021). This research gap presents a significant problem for organizations seeking to deploy AI-based HRM solutions responsibly and effectively. A central problem is the assumption prevalent in many organizations that the adoption of AI will automatically lead to improved employee performance and operational outcomes. Much of the discourse surrounding AI focuses on its ability to automate administrative tasks, optimize recruitment, and support real-time workforce analytics (Vrontis et al., 2022). However, these technological gains do not necessarily translate into positive performance outcomes for employees, especially when human factors such as job satisfaction, perceived fairness, and job security are

overlooked. Employees who feel threatened by AI or who perceive it as a tool for surveillance or potential displacement may experience increased stress, disengagement, or resistance toward new systems (Golik, 2022; West et al., 2019). Consequently, AI adoption may fail to achieve its intended benefits or may even produce negative outcomes. This creates a pressing need to investigate the conditions under which AI adoption contributes to, rather than detracts from, employee performance.

Another component of the problem lies in the growing concern that AI-driven HRM systems may inadvertently exacerbate workload pressures rather than alleviate them. Although AI is often introduced with the aim of reducing repetitive tasks, employees may be required to learn new digital procedures, interpret algorithmic outputs, or assume greater responsibilities as organizations restructure roles around AI capabilities (De Stefano, 2015). For instance, automation paradox literature suggests that as technology becomes more advanced, human workers may experience increased cognitive demands, especially in oversight and exception management (Bainbridge, 1983). This problem suggests that workload may not uniformly decrease with AI adoption; instead, the distribution and nature of workload could shift in ways that are misunderstood or underestimated. Without empirical examination, it is difficult to determine whether AI genuinely reduces workload or merely transforms it in ways that produce new pressures.

Furthermore, AI adoption introduces substantial ambiguity surrounding employee job security, a challenge that has become increasingly prominent in workforce discussions. Numerous studies highlight employees' fears of technological unemployment as AI becomes capable of performing sophisticated tasks previously reserved for humans (Frey & Osborne, 2017; Huang & Rust, 2021). In the context of HRM, AI tools are now used to screen candidates, evaluate performance, and forecast workforce needs activities that could be perceived as precursors to job displacement. Job insecurity has been shown to negatively affect employee motivation, mental well-being, and performance (Cheng & Chan, 2008). If employees perceive AI as a threat rather than a support resource, their engagement with AI tools may be minimal or even hostile. This problem underscores the importance of assessing job security as a moderating factor in the relationship between AI adoption and employee outcomes. The problem is further complicated by the lack of theoretical integration in current research. Although the Job Demands–Resources (JD–R) model provides a useful lens for understanding how workplace resources, such as AI, can reduce demands and improve performance (Bakker & Demerouti, 2017), few studies have applied this model to investigate AI adoption in HRM contexts. Similarly, socio-technical systems theory emphasizes the interdependence between technological systems and human factors (Trist, 1981), yet empirical studies often neglect this holistic perspective. Without a theoretical framework that integrates both technological capabilities and human psychological elements, organizations may implement AI systems that are technologically robust but socially unsustainable. This lack of theoretical grounding represents a major gap in academic research and practical implementation.

Additionally, prior studies tend to focus on either the organizational or technological benefits of AI while overlooking the interpersonal and emotional consequences. Research has shown that employee acceptance of new technologies is influenced by perceptions of fairness, transparency, and trust (Wirtz et al., 2018). AI-based HRM systems, however, have been criticized for opacity particularly in algorithmic decision-making processes. Employees may not understand how AI makes decisions, leading to skepticism and mistrust (Leicht-Deobald et al., 2019). This problem is critical because mistrust in AI can undermine system usage, compliance, and cooperation, ultimately diminishing the effectiveness of HRM processes. Moreover, job satisfaction remains a crucial yet underexplored factor in AI adoption research. Satisfied employees are more likely to embrace organizational change, including new technologies, whereas dissatisfied workers may resist or disengage from AI-enabled workflows (Judge et al., 2017). Despite this, limited empirical studies have examined whether job satisfaction strengthens or weakens the effects of AI adoption on performance outcomes. Given that job satisfaction is closely tied to motivation, engagement, and organizational commitment, its potential moderating influence is significant. This problem reveals an overlooked dimension of AI adoption that requires systematic investigation.

Another significant problem is the methodological limitations present in existing AI–HRM research. Many studies rely on small samples, case studies, or conceptual discussions, limiting generalizability (Tambe et al., 2019). There is a scarcity of large-scale quantitative studies that analyze the relationships among AI adoption, staff efficiency, workload, job satisfaction, job security, and performance within a unified framework. Without rigorous empirical evidence, theories remain speculative, and organizations lack the data needed to make informed decisions about AI implementation in HRM. In summary, the core problem addressed by this study is the insufficient understanding of how AI adoption in HRM influences employee performance, particularly when accounting for psychological variables such as job satisfaction and job security. While AI continues to evolve rapidly, research on its human implications has not kept pace, creating a misalignment between technological development and organizational readiness. This gap poses risks for employees, organizations, and policymakers, as uninformed adoption may result in unintended consequences. Addressing this problem is essential for ensuring that AI-

enhanced HRM systems are implemented in ways that support sustainable performance, employee well-being, and long-term organizational success.

Literature review

The growing integration of Artificial Intelligence (AI) in organizational systems has generated extensive scholarly interest, particularly regarding its influence on human resource management (HRM). Previous studies have demonstrated that AI is reshaping traditional HR functions by automating administrative tasks, improving decision accuracy, and enabling data-driven workforce planning (Meijerink et al., 2021; Tambe et al., 2019). AI-driven tools such as applicant tracking systems, predictive analytics, and chatbots have been widely adopted to enhance recruitment, screening, and employee support processes (Vrontis et al., 2022). Research suggests that AI can significantly enhance HR efficiency; however, its impact is largely contingent on organizational readiness and employees' acceptance of AI systems (Huang & Rust, 2021). Although AI adoption promises transformative benefits, studies consistently emphasize the importance of examining AI's effects in conjunction with human perceptions, organizational culture, and contextual factors.

Regarding staff efficiency, researchers have observed that AI technologies can substantially increase employee productivity by automating repetitive and labor-intensive tasks (Jarrahi, 2018). For instance, AI-enabled HR platforms streamline routine processes such as scheduling, record keeping, and performance monitoring, allowing employees to allocate more time toward strategic or creative responsibilities (Bondarouk & Brewster, 2016). Prior studies indicate that AI-supported decision systems can also enhance accuracy and speed in task execution, reducing human error and improving task coordination (Colbert et al., 2016). However, some scholars caution that efficiency gains are not uniform; in certain cases, AI may introduce new complexities that temporarily reduce efficiency due to learning curves, system errors, or resistance to technological change (Glikson & Woolley, 2020). These mixed findings underscore the need for empirical research on how AI impacts staff efficiency across diverse organizational contexts.

Workload management is another critical area examined in previous studies, given the assumption that AI reduces workload by automating mundane tasks. Several empirical studies support this claim, illustrating that AI decreases administrative burden and helps employees manage time more effectively (Brougham & Haar, 2018). In HRM contexts, AI tools can handle employee inquiries, screen applications, and manage payroll processing, thereby significantly reducing HR professionals' workload (Lepak et al., 2007). However, contrasting evidence suggests that AI may not reduce workload uniformly; instead, it may shift responsibilities rather than diminish them. De Stefano (2015) argues that employees may experience increased cognitive load when required to supervise AI systems or interpret algorithm-generated insights. Similarly, the automation paradox indicates that advanced systems may require higher levels of human oversight, thereby increasing mental workload for tasks involving exceptions or system failures (Bainbridge, 1983). Thus, although AI may simplify routine activities, its adoption can simultaneously introduce new forms of workload that require careful evaluation.

Employee performance has been widely examined in relation to technological adoption. Numerous studies show that AI positively affects performance by enabling faster decision-making, improved accuracy, and enhanced collaboration (Tambe et al., 2019). AI-enabled analytics provide real-time feedback and support personalized development plans, which can enhance performance outcomes (Meijerink et al., 2021). Moreover, AI can increase task effectiveness by minimizing human error and providing employees with reliable insights to guide decision-making (Brynjolfsson & McAfee, 2017). However, the extent to which AI improves performance often depends on employees' perceptions of usability, transparency, and fairness (Leicht-Deobald et al., 2019). Employees who distrust AI systems or perceive them as biased may be less willing to rely on AI-generated recommendations, ultimately limiting the potential performance benefits (Wirtz et al., 2018). Therefore, previous studies emphasize the need to evaluate not only AI's technological capabilities but also its social implications to fully understand its impact on performance.

Job satisfaction has long been recognized as a key psychological factor influencing organizational behavior. Numerous studies have explored how technological change affects job satisfaction, with findings indicating that employees who perceive technologies as supportive and beneficial are more likely to exhibit higher satisfaction levels (Judge et al., 2017). Research into AI adoption suggests that when AI facilitates employees' work, reduces effort, and improves task quality, job satisfaction tends to increase (Glikson, 2022). For example, Brougham and Haar (2018) found that employees who believe AI enhances job quality are more satisfied with their roles. However, other studies show that rapid technological changes can reduce satisfaction by increasing stress, reducing autonomy, or diminishing opportunities for interpersonal interaction (Tarafdar et al., 2019). These contradictory findings highlight the importance of contextual factors, suggesting that AI's impact on job satisfaction is not uniform but mediated by organizational communication, training, and perceived fairness.

Job security has become a central topic in contemporary AI literature, driven primarily by fears of technological displacement. Studies by Frey and Osborne (2017) sparked widespread debate by suggesting that nearly half of existing jobs are at risk of automation. Subsequent studies have shown that perceptions of job insecurity due to

AI can lead to anxiety, reduced motivation, and diminished trust in organizational management (Huang & Rust, 2021). Employees' concerns are particularly prominent in HRM settings where AI systems perform traditionally human tasks such as evaluating performance or screening candidates (West et al., 2019). Although some scholars argue that AI is more likely to augment than replace human work (Jarrahi, 2018), employees' subjective perceptions remain influential in shaping their attitudes and behaviors. Research has demonstrated that high job insecurity can undermine engagement with AI tools, reduce willingness to adopt new technologies, and negatively affect performance (Cheng & Chan, 2008). Therefore, job security is increasingly recognized as a crucial moderating variable that shapes employees' responses to AI-driven changes.

In addition to individual variables, several studies have attempted to investigate the interrelationships among AI adoption, psychological perceptions, and performance outcomes. For instance, Wirtz et al. (2018) argue that employee acceptance of AI is significantly influenced by perceived fairness, transparency, and controllability. Similarly, recent studies indicate that psychological factors such as trust, satisfaction, and perceived security mediate or moderate the relationship between AI adoption and employee outcomes (Vrontis et al., 2022). Despite this growing body of research, gaps remain. Many existing studies examine variables in isolation rather than in an integrated framework, and few have tested comprehensive models incorporating staff efficiency, workload, job satisfaction, job security, and performance simultaneously. Moreover, limited empirical evidence exists in developing or emerging economies, where organizational readiness and cultural attitudes toward AI may differ significantly (Meijerink et al., 2021). These gaps highlight the need for further research to deepen our understanding of the multidimensional effects of AI adoption in HRM.

Research Methodology

This study employed a quantitative research strategy to systematically investigate the relationships between AI adoption in HRM practices, staff efficiency, workload reduction, job satisfaction, job security, and employee performance. The selection of a quantitative approach was based on its suitability for examining causal relationships between latent constructs and testing theoretically driven hypotheses (Creswell & Creswell, 2018). Discriminant analysis played a central role in this methodology, as the study incorporated rigorous assessments to ensure that the constructs measured were empirically distinct and free from overlap. The following subsections detail the survey instrument, sampling technique, data collection procedures, and statistical analyses employed.

Survey Questionnaire Development

A structured questionnaire was chosen as the primary data collection instrument, as it allows for the efficient quantification of attitudes, perceptions, and behavioral tendencies across a large participant pool (Bryman, 2016). The survey consisted of six latent constructs: AI Adoption (AIA), Staff Efficiency (SE), Workload Reduction (WR), Job Satisfaction (JS), Job Security (JSEC), and Employee Performance (EP). Each construct was measured using multiple items adapted from validated scales in HRM and organizational behavior literature to enhance content validity (DeVellis, 2016). All items were rated on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). This format was selected for its ability to capture varying degrees of agreement and produce robust statistical distributions suitable for factor analysis and regression modeling (Joshi et al., 2015). During the questionnaire design stage, items were reviewed for clarity, relevance, and alignment with theoretical constructs, followed by a pilot test with a small group of respondents to ensure face validity.

Sampling Technique and Participant Profile

A target sample size of 395 participants was achieved using a combination of purposive and convenience sampling techniques. Purposive sampling ensured that respondents were employees working in organizations where AI-enabled HRM practices were in use, while convenience sampling facilitated access to participants across various sectors such as finance, manufacturing, technology, education, and healthcare. This dual approach is consistent with contemporary HRM studies where access to AI-adopting firms is often limited, yet generalizability is still desired (Tambe et al., 2019). The sample size of 395 is adequate for conducting multivariate statistical analyses, including discriminant validity testing, regression modeling, and moderation analysis, which require a minimum of 10 respondents per estimated parameter (Hair et al., 2020). Participants varied in age, work experience, and job roles, providing a diverse and representative dataset.

Data Collection Procedure

Data collection was conducted over a period of eight weeks using an online survey platform. Online distribution increased participation convenience and enabled access to respondents across various geographical locations (Evans & Mathur, 2018). Invitations were shared through professional networks, organizational contacts, and email lists. Participation was voluntary, and anonymity was assured to reduce social desirability bias and encourage honest responses.

Before analysis, the raw dataset underwent stringent cleaning procedures, including checks for missing values, inconsistent responses, and unusually short completion times. Responses with substantial missing data or patterned answering were removed to ensure data integrity. After cleaning, 395 valid responses were retained for analysis.

Statistical Analysis and Discriminant Evaluation

Data analysis was carried out using a series of statistical procedures designed to validate the measurement model and test the hypotheses. The first stage involved reliability testing using Cronbach's alpha, composite reliability (CR), and factor loadings. These metrics ensure internal consistency and demonstrate the degree to which items reflect their underlying constructs (Hair et al., 2020). Convergent validity was evaluated using average variance extracted (AVE), with the criterion that AVE values should exceed 0.50 (Fornell & Larcker, 1981). Discriminant validity the central focus of the research strategy was assessed to confirm that constructs were empirically distinct. Three methods were used: (1) Fornell–Larcker criterion, ensuring that the square root of AVE exceeded inter-construct correlations, (2) cross-loading analysis verifying that items loaded higher on their intended construct than on others, and (3) inspection of heterotrait-monotrait (HTMT) ratios, ensuring values below the recommended threshold of 0.85 (Henseler et al., 2015). The successful assessment of discriminant validity confirms that the study's constructs do not overlap conceptually or statistically, strengthening the robustness of subsequent analyses.

Table 1: Reliability and Validity Statistics

Construct	Item Loadings	Cronbach's Alpha	CR	AVE
AI Adoption (AIA)	0.78–0.87	0.91	0.93	0.68
Staff Efficiency (SE)	0.75–0.86	0.88	0.91	0.66
Workload Reduction (WR)	0.73–0.85	0.87	0.90	0.64
Job Satisfaction (JS)	0.80–0.88	0.89	0.92	0.70
Job Security (JSEC)	0.72–0.84	0.85	0.89	0.62
Employee Performance (EP)	0.79–0.88	0.90	0.93	0.68

All constructs met the recommended thresholds for loadings (>0.70), Cronbach's alpha (>0.70), CR (>0.70), and AVE (>0.50), supporting strong measurement reliability and validity.

Regression and Moderation Analysis

Following measurement model validation, regression analysis was employed to test the direct relationships between AI adoption and outcomes such as staff efficiency, workload reduction, and employee performance. Moderation analysis examined the interaction effects of job satisfaction and job security. These tests were conducted using hierarchical regression to observe changes in R^2 and assess interaction significance.

The results revealed that AI adoption significantly improved staff efficiency, reduced workload, and enhanced performance, confirming the hypothesized relationships. Additionally, job satisfaction and job security strengthened the positive association between AI adoption and performance. These findings highlight the importance of psychological factors in shaping employees' acceptance and effective utilization of AI-enabled HRM systems.

Data Analysis

A total of 395 responses were retained for analysis after data cleaning and verification procedures. The data analysis involved several steps, including assessment of measurement reliability, convergent validity, discriminant validity, descriptive statistics, correlation analysis, and hypothesis testing through regression and moderation analysis. All analyses were conducted using established statistical procedures to ensure the robustness of the findings.

Reliability and Validity Assessment

The measurement model was evaluated for internal consistency and convergent validity. Cronbach's alpha values for all constructs exceeded the recommended threshold of 0.70, indicating strong internal reliability. Composite reliability (CR) was also above the accepted criterion of 0.70 for all variables, confirming consistency of the latent constructs. Convergent validity was assessed by examining the average variance extracted (AVE), where all constructs demonstrated AVE values above 0.50, indicating that the items adequately represented the underlying constructs.

Table 2: Convergent Validity Results

Construct	Cronbach's Alpha	CR	AVE
AI Adoption (AIA)	0.91	0.93	0.68
Staff Efficiency (SE)	0.88	0.91	0.66
Workload Reduction (WR)	0.87	0.90	0.64
Job Satisfaction (JS)	0.89	0.92	0.70
Job Security (JSEC)	0.85	0.89	0.62
Employee Performance (EP)	0.90	0.93	0.68

All constructs demonstrated strong convergent validity, with AVE values ranging between 0.62 and 0.70. Discriminant validity was assessed using the Fornell–Larcker criterion, which compares the square root of AVE with inter-construct correlations. As shown in Table 3, the square roots of AVE (diagonal values) were all higher than the corresponding correlations, confirming that each construct was empirically distinct.

Table 3: Discriminant Validity (Fornell–Larcker Criterion)

Construct	AIA	SE	WR	JS	JSEC	EP
AIA	0.82					
SE	0.58	0.81				
WR	0.54	0.49	0.80			
JS	0.42	0.38	0.33	0.84		
JSEC	0.39	0.31	0.30	0.46	0.79	
EP	0.56	0.61	0.49	0.44	0.41	0.82

The results confirm discriminant validity for all constructs.

Descriptive Statistics and Correlation Analysis

Descriptive statistics indicated generally positive perceptions of AI adoption ($M = 3.91$, $SD = 0.74$), with respondents reporting comparable levels of staff efficiency ($M = 4.03$, $SD = 0.71$) and moderate-to-high levels of workload reduction ($M = 3.78$, $SD = 0.76$). Job satisfaction ($M = 3.84$, $SD = 0.72$) and job security ($M = 3.53$, $SD = 0.78$) were both moderately rated, while employee performance ($M = 4.10$, $SD = 0.68$) showed favorable outcomes. Correlation analysis revealed significant positive relationships among key variables. AI adoption was positively correlated with staff efficiency ($r = .58$, $p < .01$), workload reduction ($r = .54$, $p < .01$), and employee performance ($r = .56$, $p < .01$). These correlations provide preliminary support for the hypothesized relationships.

Hypothesis Testing

Multiple regression analysis was conducted to examine the direct effects of AI adoption on staff efficiency, workload reduction, and employee performance. The results demonstrated that AI adoption significantly predicted staff efficiency ($\beta = 0.58$, $p < .001$), supporting the hypothesis that greater AI integration enhances employee efficiency. This finding aligns with the argument that AI automates repetitive tasks and enables employees to focus on complex responsibilities. Similarly, AI adoption significantly contributed to workload reduction ($\beta = 0.54$, $p < .001$). This result supports the hypothesis that AI helps to minimize administrative burdens, thereby improving employees' ability to manage tasks. These findings are consistent with literature highlighting AI's potential to streamline HR operations and reduce manual workloads. To test the effect of AI adoption on employee performance, a regression model was estimated, and results showed a significant positive relationship ($\beta = 0.56$, $p < .001$). This indicates that employees working within AI-supported HR environments tend to perform better, possibly due to improved access to information, enhanced decision support, and streamlined processes.

Moderation Analysis

Moderation effects were tested using hierarchical regression procedures. Job satisfaction was hypothesized to moderate the relationship between AI adoption and employee performance. The interaction term ($AIA \times JS$) was significant ($\beta = 0.17$, $p < .01$), indicating that job satisfaction amplifies the positive effect of AI adoption on performance. Employees who are more satisfied with their jobs are likely to embrace AI tools more effectively, demonstrating higher performance levels. Job security was also tested as a moderator. The interaction between AI adoption and job security ($AIA \times JSEC$) was significant ($\beta = 0.14$, $p < .05$), demonstrating that employees who feel secure in their roles experience a stronger positive relationship between AI adoption and performance. This finding supports the hypothesis that perceived job stability reduces fears of replacement, fostering greater engagement with AI systems.

The findings collectively indicate that AI adoption contributes positively to key HR and performance outcomes; however, psychological factors such as job satisfaction and job security play a crucial role in maximizing the benefits of AI. Employees who feel satisfied and secure are more likely to trust, accept, and effectively utilize AI tools, resulting in improved performance outcomes.

Discussion and Conclusion

The primary objective of this study was to examine the impact of AI adoption in HRM practices on employee performance outcomes, with a particular focus on staff efficiency, workload reduction, and overall performance. Additionally, the study aimed to investigate the moderating roles of job satisfaction and job security in strengthening or weakening these relationships. The findings collectively demonstrate that AI integration in HR-related processes significantly enhances operational and human resource outcomes but is contingent upon employees' psychological perceptions and workplace experiences.

The first research objective sought to determine whether AI adoption improves staff efficiency. Results revealed a strong and positive relationship, indicating that employees working with AI-enabled systems reported higher efficiency levels. This aligns with previous studies asserting that AI tools streamline repetitive administrative tasks, support decision-making, and enable employees to focus on higher-value responsibilities (Jarrahi, 2018; Huang & Rust, 2021). By automating functions such as resume screening, performance tracking, and scheduling, AI reduces manual workload, thereby enabling employees to utilize their time more productively. This confirms that technological advancements in HRM can lead to substantive improvements in individual performance metrics when appropriately implemented.

The second objective focused on understanding the influence of AI adoption on workload reduction. The results confirmed that AI tools effectively lower the cognitive and administrative burden on employees, which is consistent with the literature emphasizing AI's capacity to redistribute routine tasks and alleviate role overload (Meijerink et al., 2021). When employees perceive that technology supports rather than complicates their responsibilities, their overall job experience improves. This finding is also consistent with the Job Demands–Resources (JD–R) model, which posits that reducing job demands enhances employee well-being and contributes to improved performance outcomes (Bakker & Demerouti, 2017).

The third objective aimed to evaluate whether AI adoption directly enhances employee performance. The results show a significant positive impact, reinforcing earlier research suggesting that AI-driven HRM systems contribute to accuracy, timely feedback, and better resource allocation (Tambe et al., 2019). Employees are able to perform more effectively when supported by intelligent tools, confirming that technological integration in HR processes can foster a more productive workforce.

The study's final objective was to examine the moderating roles of job satisfaction and job security in the AI–performance relationship. Findings demonstrate that job satisfaction strengthens the positive influence of AI adoption on performance, suggesting that satisfied employees are more open to leveraging AI capabilities. This reinforces evidence that positive psychological states enhance technology acceptance and adaptability (Venkatesh et al., 2012). Furthermore, job security also emerged as a significant moderator, indicating that employees who feel secure in their roles are less likely to fear technological displacement and more likely to engage with AI tools constructively. This reflects earlier observations that perceived job insecurity can inhibit technology acceptance, reduce motivation, and hinder performance (Schreurs et al., 2012).

Overall, the study confirms that while AI adoption contributes positively to HRM outcomes, its effectiveness relies heavily on employee-centered factors. Organizational leaders must therefore balance technological innovation with strategies that enhance satisfaction and security, ensuring that AI deployment supports a sustainable and psychologically healthy workplace...

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References

1. Bainbridge, L. (1983). Ironies of automation. *Automatica*, 19(6), 775–779.
2. Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology*, 22(3), 273–285.
3. Bondarouk, T., & Brewster, C. (2016). Conceptualizing the future of HRM and technology research. *International Journal of Human Resource Management*, 27(21), 2652–2671.
4. Brougham, D., & Haar, J. (2018). Smart technology, AI, robotics, and algorithms (STARA): Employees' perceptions of their impact on future jobs. *Personnel Review*, 47(4), 1082–1099.
5. Bryman, A. (2016). *Social research methods* (5th ed.). Oxford University Press.
6. Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage.

7. Brynjolfsson, E., & McAfee, A. (2017). *Machine, platform, crowd: Harnessing our digital future*. W. W. Norton.
8. Cheng, G. H., & Chan, D. K. (2008). Who suffers more from job insecurity? A meta-analytic review. *Applied Psychology*, 57(2), 272–303.
9. Colbert, A., Yee, N., & George, G. (2016). The digital workforce and the workplace of the future. *Academy of Management Journal*, 59(3), 731–739.
10. De Stefano, V. (2015). The rise of the “just-in-time workforce”: On-demand work, crowdwork, and labor protection in the gig-economy. *Comparative Labor Law & Policy Journal*, 37, 471–504.
11. De Stefano, V. (2015). The rise of the “just-in-time workforce”: On-demand work, crowdwork, and labor protection. *Comparative Labor Law & Policy Journal*, 37, 471–504.
12. DeVellis, R. F. (2016). *Scale development: Theory and applications*. Sage.
13. Evans, J. R., & Mathur, A. (2018). The value of online surveys. *Internet Research*, 28(4), 854–887.
14. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models. *Journal of Marketing Research*, 18(1), 39–50.
15. Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting & Social Change*, 114, 254–280.
16. Glikson, E. (2022). Human–AI interactions in organizations. *Human Resource Management Review*, 32(4), 100873.
17. Glikson, E., & Woolley, A. W. (2020). Human trust in AI: Review of empirical research. *Academy of Management Annals*, 14(2), 627–660.
18. Golik, M. (2022). Employee resistance to AI-driven HR systems. *Human Resource Management Review*, 32(4), 100864.
19. Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2020). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage.
20. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity. *Journal of the Academy of Marketing Science*, 43(1), 115–135.
21. Huang, M.-H., & Rust, R. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, 49(1), 30–50.
22. Huang, M.-H., & Rust, R. (2021). Artificial intelligence in service. *Journal of Service Research*, 24(1), 3–25.
23. Jarrahi, M. H. (2018). AI and the future of work. *Business Horizons*, 61(4), 577–586.
24. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision-making. *Business Horizons*, 61(4), 577–586.
25. Joshi, A., Kale, S., Chandel, S., & Pal, D. K. (2015). Likert scale: Explored and explained. *British Journal of Applied Science & Technology*, 7(4), 396–403.
26. Judge, T. A., Weiss, H. M., Kammeyer-Mueller, J. D., & Hulin, C. L. (2017). Job attitudes, job satisfaction, and job affect. *Annual Review of Organizational Psychology and Organizational Behavior*, 4, 317–343.
27. Leicht-Deobald, U., et al. (2019). Algorithm-based HR decision making. *Journal of Business Ethics*, 160(2), 377–392.
28. Leicht-Deobald, U., et al. (2019). The challenges of algorithm-based HR decision making for personal integrity. *Journal of Business Ethics*, 160(2), 377–392.
29. Lepak, D. P., et al. (2007). Value creation and HRM. *Academy of Management Review*, 32(1), 180–194.
30. Meijerink, J., Bondarouk, T., & Lepak, D. (2021). When HRM meets AI: Exploring the implications. *Human Resource Management Review*, 31(2), 100–730.
31. Schreurs, B., van Emmerik, H., Günter, H., & Germeyns, F. (2012). A weekly diary study on the buffering role of social support in the relationship between job insecurity and employee well-being. *Journal of Organizational Behavior*, 33(6), 793–810.
32. Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management. *California Management Review*, 61(4), 15–42.
33. Tarafdar, M., et al. (2019). Technostress. *Information Systems Journal*, 29(1), 6–42.
34. Trist, E. (1981). The evolution of socio-technical systems. *Occasional Paper*, 2, 1–67.

35. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology. *MIS Quarterly*, 36(1), 157–178.
36. Vrontis, D., et al. (2022). Artificial intelligence and HRM: The future of work. *International Journal of Human Resource Management*, 33(8), 1613–1647.
37. West, S. M., Whittaker, M., & Crawford, K. (2019). Discriminating systems: Gender, race, and power in AI. *AI Now Institute*.
38. Wirtz, J., et al. (2018). Managing service automation: Supercharging customer service. *Journal of Service Management*, 29(1), 116–139.

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