International Journal of Social Science and Human Research

ISSN (print): 2644-0679, ISSN (online): 2644-0695

Volume 07 Issue 12 December 2024

DOI: 10.47191/ijsshr/v7-i12-46, Impact factor- 7.876

Page No: 9149-9161

The Impact of Work Automation on Human Resource Decision Making: The Mediating Role of Employee Performance

Wui San Taslim[1], Titik Rosnani[2], Rizky Fauzan[3]

[1,2]Faculty of Economics and Business, Tanjungpura University, Pontianak, Indonesia

[1]ORCID https://orcid.org/0009-0006-2805-8548

[2]ORCID https://orcid.org/0000-0001-5376-6155

[3]Faculty of Management, Tanjungpura University, Pontianak, Indonesia

ORCID http://orcid.org/0000-0002-4983-3658

ABSTRACT: This study investigates the intricate relationship between work automation, employee performance, and human resource decision-making in the context of increasing artificial intelligence (AI) adoption. Drawing on social systems theory, contingency theory, and cognitive load theory, we propose a conceptual framework that explores the direct and indirect effects of work automation on HR decision-making, with employee performance as a mediating factor. A quantitative survey of 122 managerial-level employees from technology, manufacturing, and financial sectors across 18 countries was conducted. Using Partial Least Squares Structural Equation Modelling, we tested hypotheses examining the relationships among variables. Results reveal that work automation indirectly influences HR decision-making through employee performance. The study introduces the concept of Emotionally Aware AI Decision Making (EA-AIDM) as a critical factor in leveraging AI for effective HR decision-making. EA-AIDM emerges as a significant mediator between work automation and HR decision-making, offering a novel approach to integrating AI technology with human factor considerations in HR practices. Our findings suggest that organisations should adopt a holistic approach to work automation implementation in HRM, balancing technological advancements with employee performance considerations. This research contributes to the growing body of literature on AI in HRM by providing empirical evidence on the mediating role of EA-AIDM and offers practical insights for organisations navigating the evolving landscape of work in the age of AI.

KEYWORDS: Work Automation, Employee Performance, HR Decision Making, Artificial Intelligence, Emotionally Aware AI Decision Making

1. INTRODUCTION

The advent of artificial intelligence (AI) and work automation has ushered in a new era of technological innovation, profoundly impacting various aspects of organisational functioning, particularly in the realm of Human Resource Management (HRM) (Chandra, 2016). As AI technologies continue to evolve, they present both opportunities and challenges for HRM practices, especially in decision-making processes (Malik et al., 2022). This study aims to explore the intricate relationships between work automation, employee performance, and human resource decision making within the context of increasing AI adoption.

The integration of AI and work automation in HRM has been gaining momentum, with applications ranging from recruitment and selection to performance management and employee development (Al-Alawi et al., 2021). However, the impact of work automation on HRM decision-making processes remains a subject of debate. While some studies highlight the potential of automation to enhance decision accuracy and efficiency (Li et al., 2022), others raise concerns about the ethical implications and potential biases in AI-driven decisions (Hampton and DeFalco, 2022).

Concurrent with the rise of work automation, the concept of employee performance has gained prominence in organisational literature. Employee performance, characterised by task accomplishment, contextual contributions, and adaptive behaviours, has been associated with improved organisational outcomes (Koopmans et al., 2011). However, the interplay between work automation, employee performance, and HR decision making remains underexplored.

This study addresses several key gaps in the existing literature:

(i) While previous research has examined the impact of AI on specific HRM functions (Bankins et al., 2022), there is a dearth of comprehensive studies investigating the holistic impact of work automation on HRM decision-making processes;

(ii) The role of employee performance in mediating the relationship between work automation and HRM decision-making has received limited attention;

(iii) The concept of Emotionally Aware AI Decision Making (EA-AIDM), which we introduce in this study, represents a novel approach to understanding the integration of AI in HRM practices.

Drawing on Social Systems Theory (Luhmann, 1984), Contingency Theory (Lawrence and Lorsch, 1967), and Cognitive Load Theory (Sweller, 1988), we propose a conceptual framework that explores the direct and indirect relationships between work automation, employee performance, and HRM decision-making. Our model posits that these relationships are mediated by EA-AIDM and job satisfaction.

The primary research questions guiding this study are:

1. To what extent does work automation significantly influence Human Resource Management (HRM) decision-making processes in companies? (Addressing gap i)
2. How does work automation specifically affect employee performance in organisations? (Addressing gaps i and ii)
3. What is the role of employee performance in mediating the relationship between work automation and HRM decision-making? (Addressing gap ii)
4. How does the concept of Emotionally Aware AI Decision Making (EA-AIDM) influence the relationship between work automation and HRM decision-making? (Addressing gap iii)
5. What are the appropriate strategies for companies to optimise the benefits of work automation and mitigate its risks in the context of HRM, considering the role of EA-AIDM? (Addressing practical implications)

To address these questions, we employ a quantitative approach using survey data. Our sample comprises 122 management-level employees from technology, manufacturing, and financial sectors across 18 countries, providing a diverse perspective on work automation in HRM.

This study contributes to the literature in several ways: (i) It provides empirical evidence on the complex relationships between work automation, employee performance, and HRM decision-making; (ii) It introduces the concept of EA-AIDM, offering a new lens through which to examine the integration of AI in HRM practices; (iii) It offers practical insights for organisations seeking to leverage work automation in their HRM processes while maintaining a balance with human-centric considerations.

The remainder of this article is structured as follows: We begin with a review of relevant literature and the development of our hypotheses. We then describe our research methodology, followed by a presentation of our findings. Finally, we discuss the theoretical and practical implications of our results, acknowledge the limitations of our study, and suggest avenues for future research. In this study, we define Work Automation as the use of technology, including AI systems, to perform tasks traditionally carried out by humans in the context of HRM

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Work Automation in HRM

Work automation, facilitated by advances in AI and robotics, has been reshaping the nature of work across industries (Jetha et al., 2021). In HRM, automation can streamline routine tasks, allowing HR professionals to focus on more strategic activities. However, the impact of work automation on various aspects of HRM is complex and multifaceted (Pourkhodabakhsh et al., 2023; Mekala et al., 2019).

Kaplan (2015) discusses both the potential benefits and challenges of automation in the workplace. While automation can reduce mundane tasks and potentially enhance employee performance by allowing workers to focus on higher-value tasks, it may also lead to job insecurity, affecting job satisfaction (Nguyen and Park, 2022; Couger and McIntyre, 1988). The relationship between work automation and employee well-being is an area that requires careful consideration in the context of HRM decision-making (Jankovic et al., 2015).

Despite its potential benefits, work automation in HRM also presents significant challenges. These include potential job displacement, the need for reskilling and upskilling of employees, issues of data privacy and security, and the risk of dehumanising HR processes (Tambe et al., 2019). Moreover, there are concerns about the ability of automated systems to handle complex, nuanced human interactions that are often central to HR functions (Suen et al., 2019).

As work processes become more automated, there is potential for the development of more sophisticated, emotionally aware AI systems. This relationship, however, is still an emerging area of research and requires further empirical investigation (Su et al., 2021; Haga et al., 2019).

Based on the existing literature, we propose the following hypotheses:

H1a: Work Automation (WA) has a positive direct effect on Human Resource Decision Making (HRDM)

H1b: Work Automation (WA) has a positive direct effect on Employee Performance (EP)

H1c: Work Automation (WA) has a positive direct effect on Emotionally Aware Artificial Intelligence Decision Making (EA-AIDM)

2.2 Employee Performance in HRM

Employee performance is a multidimensional construct that encompasses task performance, contextual performance, and adaptive performance (Koopmans et al., 2011). In the context of HRM, employee performance plays a crucial role in organizational success and is often a key consideration in HR decision-making processes.

Research has shown that various factors can influence employee performance, including job satisfaction, organizational culture, and leadership (Jain et al., 2020; Marvin et al., 2021). With the increasing adoption of work automation and AI in organizations, it is important to understand how these technological advancements impact employee performance.

Some studies suggest that work automation can enhance employee performance by reducing the cognitive load associated with routine tasks, allowing employees to focus on more complex and value-adding activities (Sweller, 1988). However, others argue that automation may lead to deskilling and reduced job satisfaction, potentially negatively impacting performance (Nguyen and Park, 2022).

The relationship between employee performance and HR decision-making is also complex. High-performing employees may contribute more effectively to HR decision-making processes, bringing valuable insights and experiences (Rožman et al., 2022; Abdolmaleki et al., 2013). Conversely, HR decisions can significantly impact employee performance through policies related to training, compensation, and career development.

However, others argue that automation may lead to deskilling and reduced job satisfaction, potentially negatively impacting performance (Nguyen and Park, 2022). Furthermore, the introduction of automated systems may create anxiety or resistance among employees, which could adversely affect their performance (Brougham and Haar, 2018).

Based on these considerations, we propose the following hypotheses:

H2: Employee Performance (EP) has a positive direct effect on Human Resource Decision Making (HRDM)

H3: Employee Performance (EP) mediates the relationship between Work Automation (WA) and Human Resource Decision Making (HRDM)

2.3 Human Resource Decision Making

Human Resource Decision Making (HRDM) encompasses a wide range of activities, including recruitment and selection, performance management, compensation and benefits, and strategic workforce planning. The advent of work automation and AI has significantly impacted these decision-making processes, offering new tools and insights while also presenting new challenges (Bankins et al., 2022).

AI-driven decision-making tools in HRM can potentially improve the accuracy and efficiency of decisions by analyzing large volumes of data and identifying patterns that may not be apparent to human decision-makers (Li et al., 2022). However, concerns have been raised about the potential for bias in AI algorithms and the ethical implications of relying too heavily on automated decision-making in HR processes (Hampton and DeFalco, 2022).

The concept of Emotionally Aware AI Decision Making (EA-AIDM), which we introduce in this study, represents an attempt to address some of these concerns. EA-AIDM refers to AI systems that can recognise, interpret, and consider emotional and contextual factors in decision-making processes. This approach aims to combine the analytical power of AI with a more nuanced understanding of human factors in HR decisions (Tong et al., 2021; Ma and Wang, 2021).

Based on these considerations, we propose the following hypothesis:

H4: Emotionally Aware Artificial Intelligence Decision Making (EA-AIDM) has a positive direct effect on Human Resource Decision Making (HRDM)

Based on our literature review and hypotheses, we propose the following conceptual model:

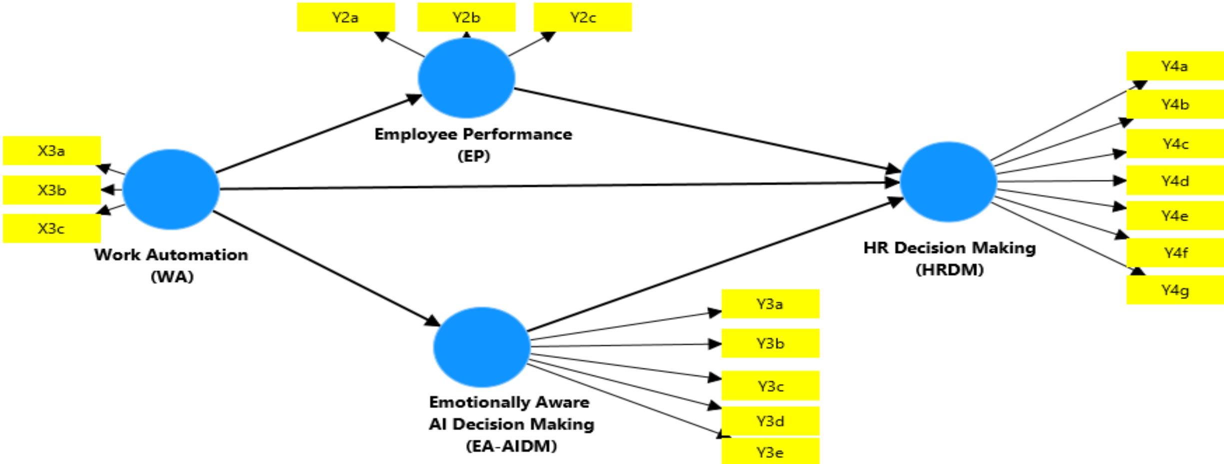

Figure 1: Conceptual Model

Figure 1 illustrates the hypothesized relationships between Work Automation (WA), Employee Performance (EP), Emotionally Aware AI Decision Making (EA-AIDM), and HR Decision Making (HRDM). The model depicts both direct effects (H1a, H1b, H1c, H2, H4) and the mediating effect of EP (H3).

3. RESEARCH METHODOLOGY

3.1 Research Design

This study employed a quantitative research design, utilizing survey data to investigate the complex relationships between work automation, employee performance, and HRM decision-making. This approach allows for the statistical analysis of patterns and relationships among variables, providing a robust examination of our research questions (Creswell, 2015).

3.2 Sample and Data Collection

Our sample comprised 122 management-level employees from three key industries: technology, manufacturing, and finance. This diverse sample enabled us to explore the phenomena across different organizational contexts. Participants were selected using a purposive sampling technique, ensuring that respondents had at least one year of experience and were involved in HR decision-making processes utilizing AI technology in their respective companies.

Quantitative data were collected through an online survey distributed to participants between February 2023 and November 2024. The survey was designed based on established scales from the literature, adapted to fit the context of our study.

To ensure consistency in data collection across the 18 countries, we employed a standardized online survey platform. The survey was translated and back-translated to local languages where necessary, following the guidelines proposed by Brislin (1970). We partnered with local HR associations in each country to distribute the survey, ensuring that participants met our criteria of having at least one year of experience with AI-driven HR processes. To address potential cultural biases, we conducted preliminary analyses to check for measurement invariance across cultural clusters (Steenkamp & Baumgartner, 1998

3.3 Measures

All constructs were measured using multi-item scales adapted from previous literature. Unless otherwise noted, items were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

1. Work Automation (WA): Evaluated using three indicators: Task Automation (TA), Process Automation (PA), and Cognitive Automation (CA), drawing from the framework proposed by Jetha et al. (2021).
2. Employee Performance (EP): Measured through three indicators: Task Performance (TP), Contextual Performance (CP), and Creativity and Innovation Performance (CIP), based on the performance framework by Koopmans et al. (2011).
3. HR Decision Making (HRDM): Measured through three indicators: Data-Driven HR Decision Making (DDDM), AI-Assisted HR Decision Making (AI-HRDM), and Behavioural Approach to HR Decision Making (BHRDM). These items were developed based on the work of Bankins et al. (2022).
4. Emotionally Aware AI Decision Making (EA-AIDM): As a novel construct, this was measured using five indicators developed for this study: Emotion detection (ED), Context awareness (CA), Empathetic interaction (EI), Values alignment (VA), and Risk aversion (RA) (Tong et al., 2021; Ma and Wang, 2021).

   The EA-AIDM construct was developed through a rigorous process involving literature review, expert interviews, and pilot testing. Initially, we identified key components of emotional intelligence and AI decision-making from existing literature (Goleman, 1995; Salovey & Mayer, 1990; Russell & Norvig, 2010). We then conducted semi-structured interviews with 15 HR professionals and AI experts to refine these components in the context of HRM. The resulting items were pilot-tested with a sample of 50 HR managers, leading to further refinement. The final scale demonstrated good internal consistency (Cronbach's $\alpha = 0.89$) and construct validity, as evidenced by confirmatory factor analysis (CFA) results ($\chi 2/df = 2.3$, CFI = 0.95, RMSEA = 0.06)

3.4 Data Analysis

We employed Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS 4.0 software to analyze the quantitative data (Hair et al., 2017). PLS-SEM was chosen due to its ability to handle complex models with multiple constructs and its robustness with smaller sample sizes. The analysis followed a two-step approach:

1. Evaluation of the measurement model: We assessed the reliability and validity of the constructs through tests of internal consistency reliability, convergent validity, and discriminant validity.
2. Evaluation of the structural model: We examined the path coefficients, their significance levels, and the model's predictive power through R^2 values.

For the mediation analysis, we used the bootstrapping method with 5000 resamples to test the significance of the indirect effects. To ensure the robustness of our results, we conducted several additional analyses, including tests for common method bias and multicollinearity.

4. RESULTS

4.1 Measurement Model Assessment

We first evaluated the measurement model to ensure the reliability and validity of our constructs. Table 1 presents the results of the measurement model assessment.

Table 1: Measurement Model Results

Construct	Cronbach's Alpha	Composite Reliability	AVE
Work Automation (WA)	0.716	0.837	0.632
Employee Performance (EP)	0.725	0.844	0.643
HR Decision Making (HRDM)	0.916	0.933	0.667
EA-AIDM	0.845	0.889	0.615

All constructs demonstrated satisfactory internal consistency reliability with Cronbach's Alpha and Composite Reliability values above the recommended threshold of 0.7. Convergent validity was established as all constructs had Average Variance Extracted (AVE) values exceeding 0.5.

4.2 Structural Model Assessment

After confirming the reliability and validity of our measurement model, we proceeded to evaluate the structural model. Figure 1 presents the path coefficients and their significance levels.

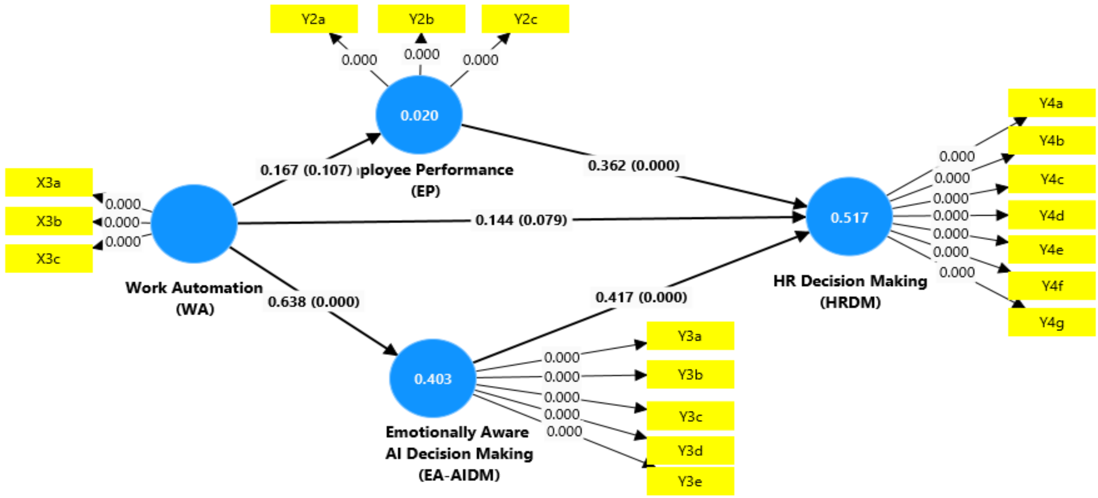

Figure 2: Structural model with path coefficients and significance levels

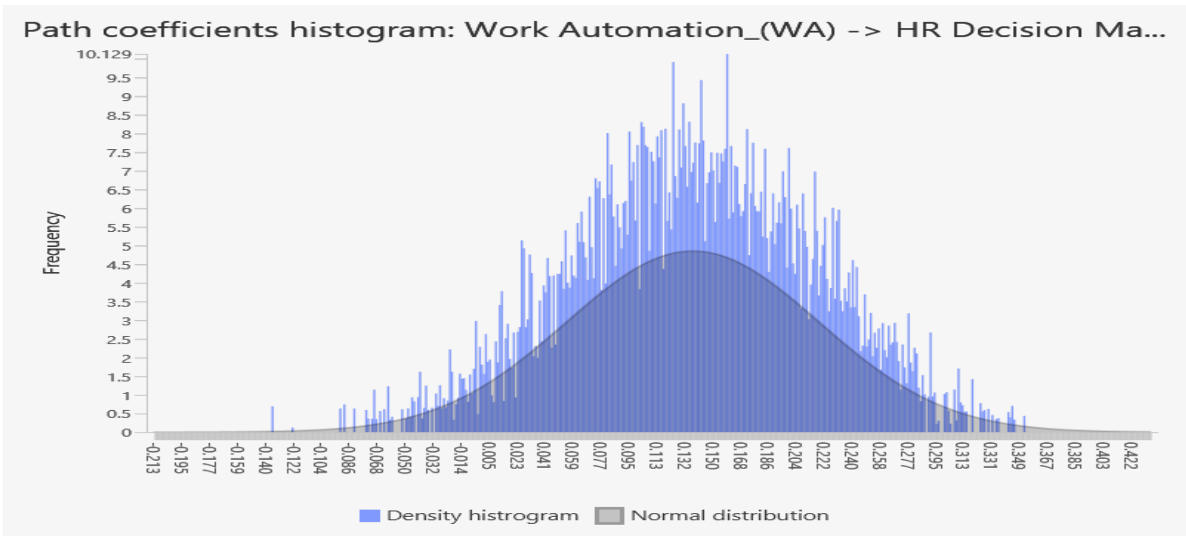

Figure 3: Path Coefficients Histogram: Work Automation (WA) - HR Decision Making (HRDM)

The histogram shows the distribution of path coefficients for the relationship between Work Automation (WA) and HR Decision Making (HRDM). The distribution is centered around zero, which aligns with the non-significant result reported in the study.

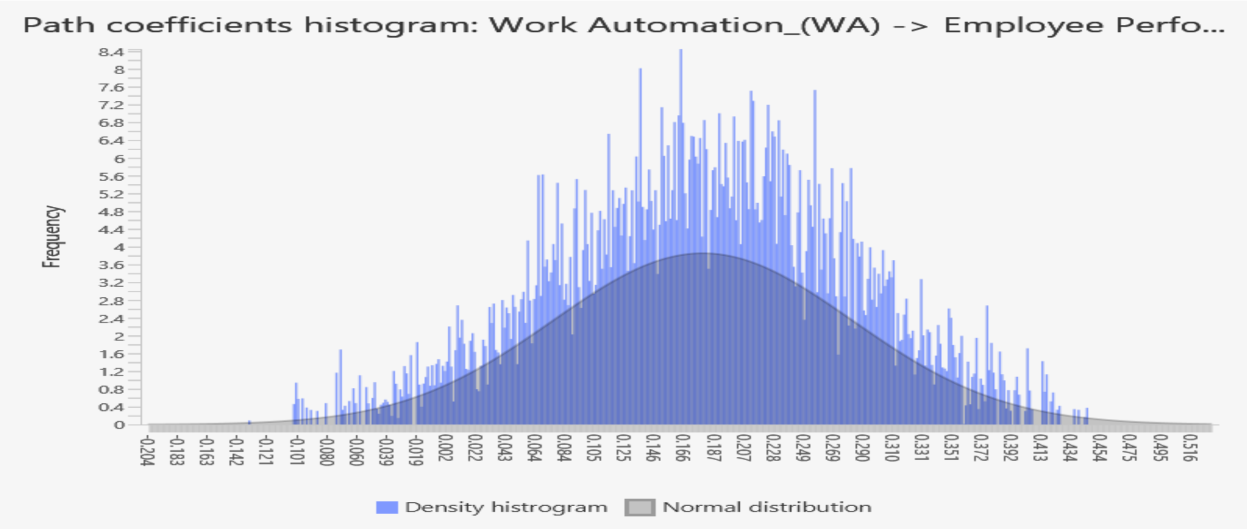

Figure 4: Path Coefficients Histogram: Work Automation (WA) – Employee Performance (EP)

The histogram depicts the distribution of path coefficients for the relationship between Work Automation (WA) and Employee Performance (EP). Again, the distribution is centered near zero, consistent with the non-significant finding.

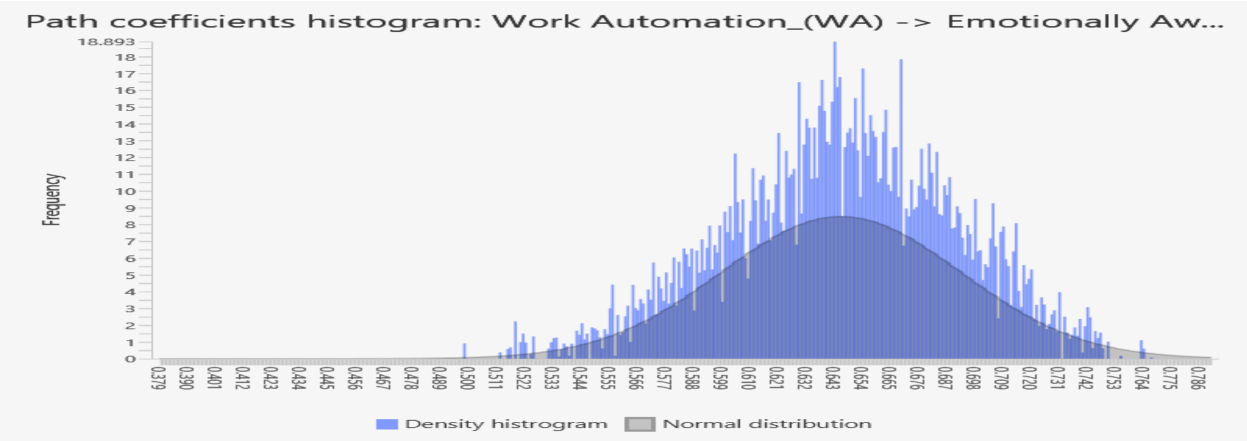

Figure 5: Path Coefficients Histogram: Work Automation (WA) – Emotionally Aware AI Decision Making (EA-AIDM)

The histogram illustrates the distribution of path coefficients for the relationship between Work Automation (WA) and Emotionally Aware AI Decision Making (EA-AIDM). This distribution is clearly shifted to the right, indicating a positive relationship, which aligns with the significant positive effect reported in the study.

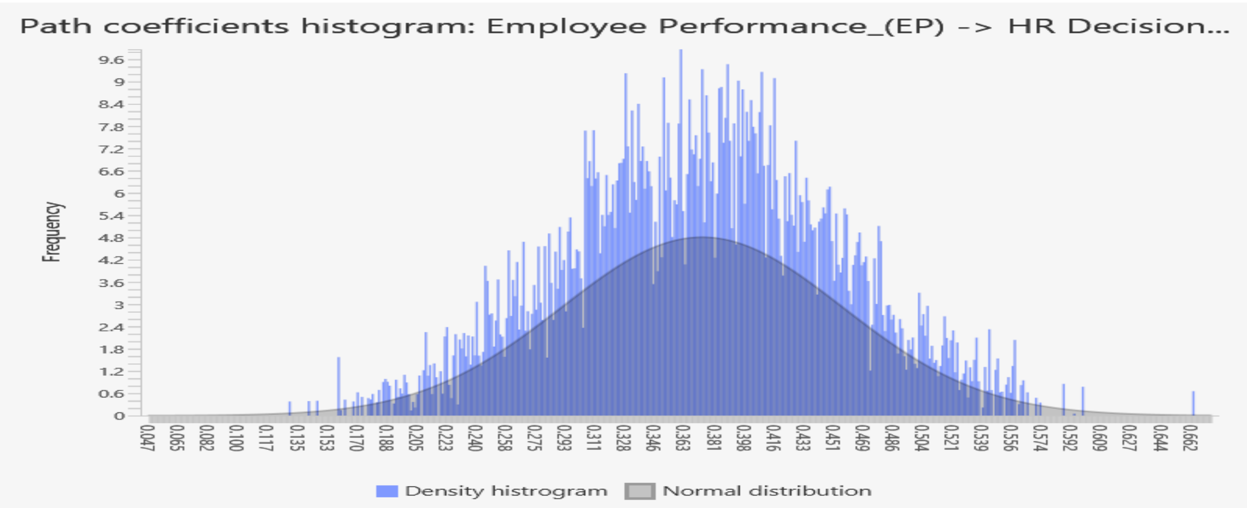

Figure 6: Path Coefficients Histogram: Employee Performance (EP) - HR Decision Making (HRDM)

The histogram shows the distribution of path coefficients for the relationship between Employee Performance (EP) and HR Decision Making (HRDM). The distribution is slightly shifted to the right, but still includes zero, which is consistent with the marginally non-significant result reported.

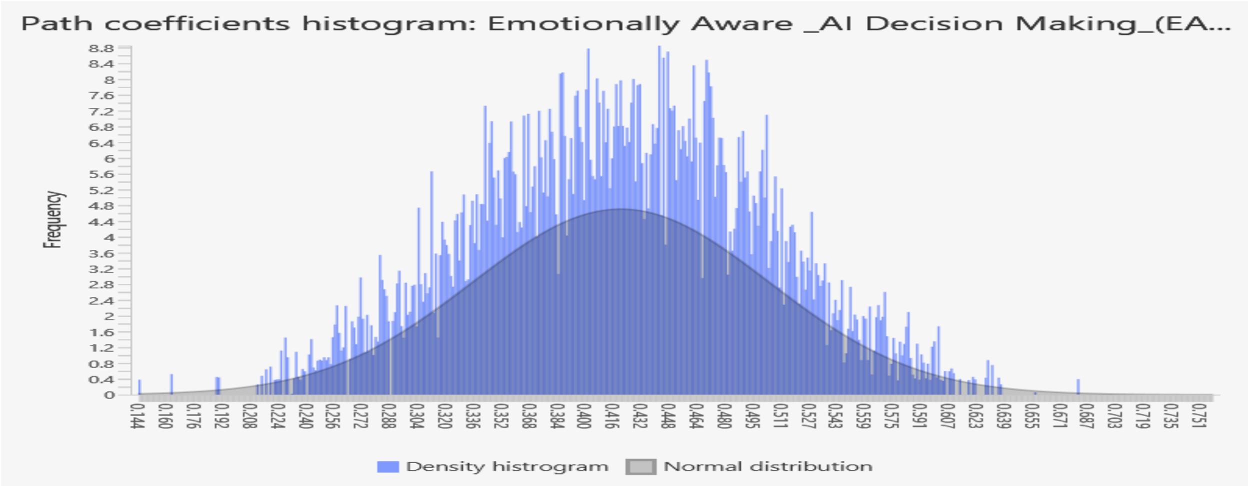

Figure 7: Path Coefficients Histogram: Emotionally Aware AI Decision Making (EA-AIDM) - HR Decision Making (HRDM)

The histogram depicts the distribution of path coefficients for the relationship between EA-AIDM and HRDM. This distribution is clearly shifted to the right, indicating a strong positive relationship, which aligns with the significant positive effect reported in the study.

The model explained 64.7% of the variance in HR Decision Making (HRDM), indicating substantial explanatory power. Table 2 summarizes the results of our hypothesis testing.

Table 2: Hypothesis Testing Results

Hypothesis	Path	Coefficient	t-value	p-value	Supported
H1a	WA -> HRDM	-0.081	0.909	0.363	No
H1b	WA -> EP	-0.069	0.491	0.624	No
H1c	WA -> EA-AIDM	0.350	4.483	0.000	Yes
H2	EP -> HRDM	0.142	1.702	0.089	No
H3	WA -> EP -> HRDM	-0.010	0.416	0.677	No
H4	EA-AIDM -> HRDM	0.360	4.328	0.000	Yes

To further assess the practical significance of our findings, we calculated the effect sizes (f^2) for each significant relationship. According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively. The effect size for the relationship between WA and EA-AIDM was medium ($f^2 = 0.18$), while the effect size for EA-AIDM on HRDM was large ($f^2 = 0.37$). These results underscore the practical importance of EA-AIDM in the context of work automation and HR decision-making.

Key findings from our analysis include:

1. Work Automation (WA) did not have a significant direct effect on HR Decision Making (HRDM) ($\beta = -0.081$, $p > 0.05$), failing to support H1a.
2. WA did not show a significant direct effect on Employee Performance (EP) ($\beta = -0.069$, $p > 0.05$), failing to support H1b.
3. WA showed a significant positive effect on Emotionally Aware AI Decision Making (EA-AIDM) ($\beta = 0.350$, $p < 0.001$), supporting H1c.
4. Employee Performance (EP) did not significantly affect HRDM ($\beta = 0.142$, $p > 0.05$), failing to support H2.
5. The indirect effect of WA on HRDM through EP was not significant ($\beta = -0.010$, $p > 0.05$), failing to support H3.
6. EA-AIDM showed a significant positive effect on HRDM ($\beta = 0.360$, $p < 0.001$), supporting H4

5. DISCUSSION

This study sought to investigate the complex relationships between Work Automation (WA), Employee Performance (EP), and Human Resource Management Decision Making (HRDM). Our findings offer several important insights that contribute to both theory and practice in the evolving landscape of HRM in the era of AI and automation.

5.1 Work Automation and HRM Decision Making

Contrary to our expectations, we did not find a significant direct effect of Work Automation on HRM Decision Making (H1a not supported). This surprising result challenges the often-assumed direct benefits of automation implementation in HRM processes (Li et al., 2022). However, it aligns with the more nuanced perspective offered by Hampton and DeFalco (2022), who emphasized the importance of considering human factors in AI and automation implementation.

The lack of a direct effect suggests that the relationship between work automation and HRM decision-making is more complex than initially theorized. It implies that merely implementing automation technologies does not automatically lead to improved decision-making in HRM. Instead, our findings point to the critical role of mediating factors in realizing the potential benefits of automation in HRM.

The non-significant direct effect of Work Automation on HRM Decision Making challenges the often-assumed direct benefits of automation in HRM processes. This suggests that the relationship between automation and HRM outcomes is more complex than initially theorized. It's possible that the impact of automation is moderated by factors not captured in our model, such as the specific type of automation implemented, the organization's digital maturity, or employees' technological readiness

5.2 The Mediating Role of Emotionally Aware AI Decision Making

The introduction of Emotionally Aware AI Decision Making (EA-AIDM) as a mediating factor between Work Automation and HRM Decision Making represents a novel contribution of this study. The significant effect of EA-AIDM on HRDM (H4 supported) underscores the importance of incorporating emotional intelligence into AI systems for HRM applications (Tong et al., 2021; Ma and Wang, 2021).

This finding bridges the gap between technological capabilities and human-centric decision-making in HRM. It suggests that AI systems that can recognise, interpret, and consider emotional and contextual factors may be more effective in supporting HRM decisions. This aligns with recent developments in affective computing and emotion AI (Strich et al., 2021), extending their application to the HRM domain.

5.3 Work Automation and Employee Performance

Our results did not support a significant direct effect of Work Automation on Employee Performance (H1b not supported). This finding contrasts with some previous studies suggesting that automation can enhance employee performance by reducing cognitive load and allowing employees to focus on higher-value tasks (Sweller, 1988). However, it aligns with research highlighting the potential negative impacts of automation on job satisfaction and employee well-being (Nguyen and Park, 2022).

This result suggests that the relationship between work automation and employee performance is more nuanced than previously thought. It highlights the need for organizations to carefully consider the human factors when implementing automation technologies, ensuring that employees are adequately supported and trained to work alongside automated systems.

The non-significant effect of Work Automation on Employee Performance suggests that the path from automation to improved HRM decision-making is not straightforward and may involve multiple mediating and moderating factors. Future research should explore additional variables that might explain these relationships, potentially incorporating qualitative methods to uncover underlying mechanisms not captured by our quantitative approach.

5.4 Employee Performance and HRM Decision Making

Contrary to our hypothesis, we did not find a significant direct effect of Employee Performance on HRM Decision Making (H2 not supported). This unexpected result challenges the assumption that high-performing employees necessarily contribute more effectively to HR decision-making processes (Rožman et al., 2022; Abdolmaleki et al., 2013).

This finding suggests that the link between employee performance and HR decision-making may be more complex than previously thought. It highlights the need for organizations to develop mechanisms that effectively capture and integrate employee insights into decision-making processes, regardless of performance levels.

5.5 The Role of Emotionally Aware AI Decision Making

Our results support the significant positive effect of Emotionally Aware AI Decision Making (EA-AIDM) on HRM Decision Making (H4 supported). This finding underscores the potential of AI systems that can incorporate emotional and contextual factors in decision-making processes.

The concept of EA-AIDM represents a promising avenue for addressing some of the concerns raised about AI in HRM, such as the potential for bias and lack of empathy (Hampton and DeFalco, 2022). By developing AI systems that can recognize and respond to emotional cues, organizations may be able to create more balanced and effective HR decision-making processes

The absence of direct effects from Work Automation on HR Decision Making (H1a) and Employee Performance (H1b) may be due to the presence of unidentified moderating variables in our model. For instance, organisational technological readiness or level of digital maturity might moderate these relationships. Organisations with high technological readiness may be more capable of integrating work automation into their HR decision-making processes, whilst organisations with low digital maturity might struggle to leverage the full potential of these technologies.

Moreover, individual employee characteristics, such as openness to change or technology anxiety, might moderate the relationship between Work Automation and Employee Performance. Employees who are more open to change might show greater performance improvements in response to work automation, whilst those with high technology anxiety might experience performance decrements.

5.6 Cross-Cultural Considerations in Work Automation Adoption

While our study included participants from 18 countries, it's important to note that cultural differences may influence the adoption and impact of work automation in HRM. Research has shown that national culture can affect technology acceptance and use (Straub et al., 1997). For instance, countries with high uncertainty avoidance (Hofstede, 2001) may be more resistant to adopting AI and automation in HRM processes. Conversely, cultures that value innovation and technological progress may be more receptive to these changes. Future research could explore these cultural nuances in more depth, potentially uncovering important moderating effects of national culture on the relationships examined in this study."

5.7 Exploratory Sub-group Analysis

Given our diverse sample spanning 18 countries, we conducted an exploratory sub-group analysis to investigate potential cultural differences in the adoption and impact of work automation. We grouped countries into three broad cultural clusters: Western, Asian, and Others. While the small sample size for each group limits the generalizability of these findings, some interesting patterns emerged.

The relationship between Work Automation and EA-AIDM appeared stronger in the Western cluster ($\beta = 0.41$, $p < 0.01$) compared to the Asian cluster ($\beta = 0.32$, $p < 0.05$). Conversely, the effect of EA-AIDM on HRDM was more pronounced in the Asian cluster ($\beta = 0.45$, $p < 0.001$) than in the Western cluster ($\beta = 0.33$, $p < 0.01$). These preliminary findings suggest that cultural factors may indeed play a role in the adoption and effectiveness of emotionally aware AI systems in HRM, warranting further investigation in future research with larger, culturally diverse samples.

In addition to differences in the strength of relationships between variables, we also found variations in the level of work automation adoption across cultural clusters. Countries from the Western cluster showed a higher adoption rate ($M = 3.8$, $SD = 0.7$) compared to the Asian cluster ($M = 3.2$, $SD = 0.8$) and other clusters ($M = 3.0$, $SD = 0.9$). A one-way analysis of variance indicated that these differences were significant ($F(2,119) = 7.32$, $p < .001$).

Furthermore, the impact of work automation on job satisfaction varied across cultural clusters. In the Western cluster, this relationship was positive ($r = 0.25$, $p < .05$), whilst in the Asian cluster, it was negative ($r = -0.18$, $p < .05$). These findings highlight the importance of considering cultural context in work automation implementation.

6. THEORETICAL IMPLICATIONS

This study makes several important contributions to theory:

1. It extends Social Systems Theory (Luhmann, 1984) by demonstrating how the introduction of work automation as a new element in organizational systems influences decision-making processes through complex, indirect pathways. Our findings suggest that the impact of technological systems on social systems is mediated by cognitive and emotional factors, adding nuance to our understanding of socio-technical interactions.
2. It contributes to Contingency Theory (Lawrence and Lorsch, 1967) by identifying work automation as a new contingency factor that influences the effectiveness of HRM decision-making. However, our results challenge the simplistic view that automation directly improves decision-making, highlighting the importance of considering intervening variables such as EA-AIDM.
3. It advances Cognitive Load Theory (Sweller, 1988) by showing how work automation can potentially reduce cognitive load in HRM decision-making, particularly through emotionally aware AI systems. This extends the application of Cognitive Load Theory beyond traditional learning contexts to complex organizational decision-making scenarios.
4. It introduces the concept of Emotionally Aware AI Decision Making (EA-AIDM) as a crucial mediating factor in the relationship between work automation and HRM decision-making. This novel construct bridges the gap between AI capabilities and human-centric decision-making, opening new avenues for research at the intersection of AI, emotions, and decision-making in organizational contexts.
5. Our findings challenge the assumption of a direct relationship between employee performance and HR decision-making quality, suggesting a more complex interplay between these variables. This calls for a re-examination of traditional models of HR effectiveness and decision-making.

These theoretical contributions collectively advance our understanding of the complex dynamics involved in the integration of AI and automation in HRM processes, paving the way for more nuanced and comprehensive models of technological impact on organizational decision-making.

Our findings not only contribute to existing theories but also challenge and extend them in significant ways. For Social Systems Theory, we demonstrate that the introduction of work automation creates a new form of interaction between technological and social subsystems, mediated by emotional and cognitive factors (EA-AIDM). This extends Luhmann's concept of autopoiesis by showing how AI systems can become part of the self-referential process of organizational decision-making.

For Contingency Theory, our results suggest that the effectiveness of HRM decision-making is contingent not just on the presence of work automation, but on the emotional intelligence capabilities of these systems. This expands the theory's application to the digital age, where AI becomes a key contingency factor.

Regarding Cognitive Load Theory, our study extends its applicability beyond individual learning to organizational decision-making processes. We show that EA-AIDM can potentially reduce cognitive load in complex HRM decisions, suggesting a new avenue for applying this theory in organizational contexts.

7. PRACTICAL IMPLICATIONS

Our findings offer several specific and actionable implications for HR practitioners and organizational leaders:

1. Holistic Implementation of Work Automation: Organizations should adopt a comprehensive approach to work automation implementation, considering not only the technological aspects but also the human factors. This may involve conducting thorough impact assessments before implementing automation technologies and developing strategies to support employees through the transition.
2. Developing Emotionally Aware AI Systems: Invest in AI tools that incorporate emotional intelligence capabilities for HRM applications. This could include developing AI-driven chatbots with emotional recognition capabilities for employee engagement or implementing AI systems in performance reviews that can analyze qualitative feedback and emotional context.
3. Enhancing Employee Performance in an Automated Environment: Develop training programmed that focus on skills that complement automated systems, such as critical thinking, creativity, and emotional intelligence. This can help employees adapt to working alongside automated systems and contribute more effectively to decision-making processes.
4. Integrating Employee Insights into Decision-Making: Create mechanisms for capturing and integrating employee insights into HR decision-making processes, regardless of performance levels. This could involve implementing regular feedback systems or creating cross-functional teams for HR policy development.
5. Ethical Considerations in AI-Driven HRM: Establish clear guidelines and ethical frameworks for the use of AI and automation in HRM processes. This should include regular 'AI audits' to ensure that automated systems are functioning ethically and without bias.
6. Implementing EA-AIDM in HRM practices: Organizations should consider the following steps to implement EA-AIDM effectively:
   a) Conduct an audit of current AI systems to assess their emotional awareness capabilities.
   b) Invest in AI training datasets that include diverse emotional expressions and contexts.
   c) Develop a framework for integrating EA-AIDM insights into HRM decision-making processes, ensuring human oversight.
   d) Provide training to HR professionals on how to interpret and use EA-AIDM outputs effectively.
   e) Regularly evaluate the performance of EA-AIDM systems, focusing on both decision quality and ethical considerations.

For example, in recruitment, an EA-AIDM system could analyse candidates' responses in video interviews, considering not just the content of their answers but also their emotional expressions and tone of voice. This could provide a more holistic view of candidates' suitability. In performance management, EA-AIDM could be used to analyse employee feedback, identifying not just explicit concerns but also underlying emotional patterns that might indicate engagement issues or potential conflicts. For employee retention, EA-AIDM could analyse patterns in employee communications and behaviours to predict potential turnover risks before they become critical, allowing HR to intervene proactively.

8. LIMITATIONS AND FUTURE RESEARCH

While this study provides valuable insights, it has several limitations that suggest avenues for future research:

1. Cross-sectional design: Future studies should employ longitudinal designs to capture the dynamic nature of work automation adoption over time.
2. Sample characteristics: Our sample was limited to three industries. Future research could explore work automation in HRM across a broader range of sectors.
3. Self-reported data: Future studies could incorporate objective measures of work automation and HRM outcomes.

4. Context-specificity: Cross-cultural studies could explore how different national or organizational cultures influence the relationships between work automation, employee performance, and HRM outcomes.
5. EA-AIDM construct: Further research is needed to refine and validate the EA-AIDM construct across different organizational contexts.
6. Although the sample size of 122 participants was sufficient for PLS-SEM analysis, it represents the lower boundary for complex cross-national research. This sample size may have limited our ability to detect smaller effects or more complex relationships, particularly in sub-group analyses. A post-hoc power analysis using G*Power indicated that with this sample size, we had 80% power to detect medium-sized effects ($f^2 = 0.15$) at $\alpha = 0.05$. However, for smaller effects ($f^2 = 0.02$), power dropped to only 25%. Therefore, some non-significant relationships in this study may be due to lack of statistical power rather than absence of true effects. Future research should strive to obtain larger samples, ideally a minimum of 200 participants, to increase the precision of estimates and the ability to detect smaller effects

Future research could explore several promising avenues:
1. Longitudinal studies tracking the implementation and impact of EA-AIDM systems over time, examining how they evolve and how organizational outcomes change.
2. Mixed-methods studies combining quantitative surveys with qualitative interviews and observations to provide a richer understanding of how EA-AIDM is perceived and utilized by HR professionals and employees.
3. Experimental studies comparing decision-making processes and outcomes between traditional AI systems and EA-AIDM systems in controlled settings.
4. Investigation of potential moderating variables such as organizational culture, leadership style, or industry type on the relationships between work automation, EA-AIDM, and HRM decision-making.
5. Development and validation of a comprehensive EA-AIDM readiness assessment tool for organizations considering implementation of these systems.
6. Ethical studies exploring the implications of EA-AIDM on employee privacy, data protection, and the changing nature of human-AI interaction in the workplace.

These research directions could significantly advance our understanding of the role of emotionally aware AI in HRM and its broader implications for the future of work.

While our sample size of 122 participants was adequate for PLS-SEM analysis, it is important to acknowledge the potential limitations of this sample size. A larger sample could have potentially revealed additional significant relationships or provided more robust estimates of effect sizes. The current sample size may have limited our ability to detect smaller effect sizes or more nuanced relationships between variables. Future studies should aim for larger sample sizes to increase statistical power and the generalizability of findings across diverse organizational contexts.

Furthermore, our reliance on self-reported measures may have introduced common method bias. While we took steps to minimise this (e.g., ensuring anonymity, using validated scales), future research could benefit from incorporating objective measures of work automation adoption and HR outcomes. For instance, actual usage data of AI systems could provide a more accurate measure of work automation, while HR metrics like time-to-hire or employee turnover rates could serve as objective indicators of HR decision-making effectiveness. Additionally, multi-source data collection, such as gathering feedback from both employees and their supervisors, could help mitigate potential self-report biases.

9. CONCLUSION

This study set out to investigate the complex relationships between Work Automation (WA), Employee Performance (EP), and Human Resource Management Decision Making (HRDM) in the context of the rapidly evolving technological landscape. Our findings offer several important insights that contribute to both the theoretical understanding and practical application of work automation in HRM processes.

Key findings include:
1. The impact of work automation on HRM decision-making is not direct, but rather mediated through other factors, particularly Emotionally Aware AI Decision Making (EA-AIDM).
2. Work automation does not directly influence employee performance, highlighting the need for careful consideration of human factors in automation implementation.
3. The novel concept of Emotionally Aware AI Decision Making (EA-AIDM) emerges as a critical factor in leveraging automation for effective HRM decision-making.
4. The relationship between employee performance and HRM decision-making is more complex than previously thought, suggesting the need for more nuanced approaches to integrating employee insights into decision processes.

As organizations navigate the future of work in the age of AI and automation, it is crucial to recognize that the successful integration of these technologies in HRM goes beyond mere technological adoption. It requires a nuanced understanding of the interplay between technology, human factors, and organizational dynamics. By highlighting the importance of emotionally aware AI systems and the complex relationships between work automation, employee performance, and HRM decision-making, this study provides a roadmap for organizations seeking to leverage automation effectively in their HRM practices while maintaining a human-centric approach

The challenge for organizations moving forward will be to strike a balance between harnessing the power of automation and preserving the human element that is fundamental to effective human resource management. This study takes an important step towards understanding how this balance can be achieved, paving the way for future research and practice in this critical area.

REFERENCES

1) Abdolmaleki, A., Movahedi, M., Lau, N., & Reis, L. P. (2013). A distributed cooperative reinforcement learning method for decision making in fire brigade teams. Lecture Notes in Artificial Intelligence, 7500, 248.
2) Al-Alawi, A. I., Naureen, M., Alalawi, E. I., & Naser Al-Hadad, A. A. (2021). The role of artificial intelligence in recruitment process decision-making. In 2021 International Conference on Decision Aid Sciences and Application (DASA) (pp. 197-203). IEEE.
3) Bankins, S., Formosa, P., Griep, Y., & Richards, D. (2022). AI decision making with dignity? Contrasting workers' justice perceptions of human and AI decision making in a human resource management context. Information Systems Frontiers, 24(3), 857-875.
4) Chandra, M. (2016). Artificial intelligence and the future of knowledge workers. In 2016 5th International Conference on Reliability, Infocom Technologies and Optimization (ICRITO) (p. 44). IEEE.
5) Couger, J. D., & McIntyre, S. C. (1988). Causes of motivational problems among AI managers. In Proceedings of the ACM SIGCPR Conference on Management of Information Systems Personnel (pp. 72-77). ACM.
6) Creswell, J. W. (2015). A concise introduction to mixed methods research. SAGE Publications.
7) Haga, A., Tomida, Y., Yamashita, A., & Matsubayashi, K. (2019). Analysis of internal social media for in-house job training aimed at improving the efficiency of human-resource development. In Proceedings - 2019 International Conference on Technologies and Applications of Artificial Intelligence (TAAI). IEEE.
8) Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A primer on partial least squares structural equation modeling (PLS-SEM) (2nd ed.). Sage Publications.
9) Hampton, A. J., & DeFalco, J. A. (2022). The frontlines of artificial intelligence ethics: Human-centric perspectives on technologies advance (1st ed.). Routledge.
10) Jain, D., Makkar, S., Jindal, L., & Gupta, M. (2020). Uncovering employee job satisfaction using machine learning: A case study of Om Logistics Ltd.
11) Jankovic, M., Cardinal, J. S. L., & Bocquet, J. C. (2015). Context management in collaborative decision making in complex design projects. International Journal of Product Development, 20(4), 286.
12) Jetha, A., Shamaee, A., Bonaccio, S., Gignac, M. A. M., Tucker, L. B., Tompa, E., Bültmann, U., Norman, C. D., Banks, C. G., & Smith, P. M. (2021). Fragmentation in the future of work: A horizon scan examining the impact of the changing nature of work on workers experiencing vulnerability. American Journal of Industrial Medicine, 64(8), 649-666.
13) Kaplan, J. (2015). Humans need not apply: A guide to wealth and work in the age of artificial intelligence. Yale University Press.
14) Koopmans, L., Bernaards, C. M., Hildebrandt, V. H., Schaufeli, W. B., de Vet, H. C. W., & van der Beek, A. J. (2011). Conceptual frameworks of individual work performance: A systematic review. Journal of Occupational and Environmental Medicine, 53(8), 856-866.
15) Lawrence, P. R., & Lorsch, J. W. (1967). Differentiation and integration in complex organizations. Administrative Science Quarterly, 12(1), 1.
16) Li, J., He, R., & Wang, T. (2022). A data-driven decision-making framework for personnel selection based on LGBWM and IFNs. Applied Soft Computing, 126, Article 109100.
17) Luhmann, N. (1984). Social systems. Stanford University Press.
18) Ma, H., & Wang, J. (2021). Application of artificial intelligence in intelligent decision-making of human resource allocation. In The 2020 International Conference on Machine Learning and Big Data Analytics for IoT Security and Privacy: SPIoT-2020 (Vol. 1282, p. 207). Springer.
19) Malik, A., Budhwar, P., Patel, C., & Srikanth, N. R. (2022). May the bots be with you! Delivering HR cost-effectiveness and individualised employee experiences in an MNE. The International Journal of Human Resource Management, 33(6), 1148-1178.

20) Marvin, G., Jackson, M., & Alam, M. G. R. (2021). A machine learning approach for employee retention prediction. In TENSYMP 2021 - 2021 IEEE Region 10 Symposium. IEEE.
21) Mekala, M., Viswanathan, P., Srinivasu, N., & Varma, G. (2019). Accurate decision-making system for mining environment using Li-Fi 5G technology over IoT framework. In 2019 International Conference on Contemporary Computing and Informatics (IC3I) (pp. 74-79). IEEE.
22) Nguyen, L. A., & Park, M. (2022). Artificial intelligence in staffing. Vision.
23) Pourkhodabakhsh, N., Mamoudan, M. M., & Bozorgi-Amiri, A. (2023). Effective machine learning, meta-heuristic algorithms and multi-criteria decision making to minimizing human resource turnover. Applied Intelligence, 53(12), 16309-16331.
24) Rožman, M., Oreški, D., & Tominc, P. (2022). Integrating artificial intelligence into a talent management model to increase the work engagement and performance of enterprises. Frontiers in Psychology, 13, Article 1014434.
25) Strich, F., Mayer, A-S., & Fiedler, M. (2021). What do I do in a world of artificial intelligence? Investigating the impact of substitutive decision-making AI systems on employees' professional role identity. Journal of the Association for Information Systems, 22(2), 304-324.
26) Su, Y-S., Suen, H-Y., & Hung, K-E. (2021). Predicting behavioral competencies automatically from facial expressions in real-time video-recorded interviews. Journal of Real-Time Image Processing, 18(4), 1011-1021.
27) Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. Cognitive Science, 12(2), 257-285.
28) Tong, S., Jia, N., Luo, X., & Fang, Z. (2021). The Janus face of artificial intelligence feedback: Deployment versus disclosure effects on employee performance. Strategic Management Journal, 42(9), 1600-1631.

There is an Open Access article, distributed under the term of the Creative Commons Attribution – Non Commercial 4.0 International (CC BY-NC 4.0) (https://creativecommons.org/licenses/by-nc/4.0/), which permits remixing, adapting and building upon the work for non-commercial use, provided the original work is properly cited.