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How AI-Enabled HRM Practices Enhance Employee Sustainable Performance: The Roles of Trust in AI and Technology Readiness

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ABSTRACT

Objective: This study investigates the influence of artificial intelligence (AI)-enabled human resource management (HRM) practices on employee sustainable performance, while examining the mediating role of trust in AI and the moderating role of technology readiness. Drawing upon the technology acceptance model and the unified theory of acceptance and use of technology (UTAUT), this research explores how employees' psychological trust in AI-driven HRM systems and their predisposition toward technology collectively shape the relationship between AI-enabled HRM practices and sustainable employee outcomes across diverse industries in Pakistan.

Design/methodology/approach: The study included a cross-sectional quantitative survey of 310 employees from Pakistan's manufacturing, supply chain, healthcare, technology, and finance sectors. The data was analyzed using PLS-SEM with Smart PLS 4.8.0, and predefined measurement criteria were utilized to assess validity and reliability. The structural model investigated direct, mediating, and moderating effects using bootstrapping techniques.

Findings: The AI-enabled HRM practices considerably boost employee consistent and sustainable performance ($\beta = 0.498$, $p < 0.001$), and faith in AI strongly mediates this relationship ($\beta = 0.134$, $p < 0.01$). where, technology readiness does not strongly mitigate the connect ($\beta = -0.025$, $p > 0.05$). Hence, the employee trust—rather than technological prowess is the key to having long-term performance advantages from AI-enabled HRM.

Practical implications: By include trust as a mediator and technical preparedness as a moderator in the relationship between employee sustainable performance and AI-enabled HRM practices, this study contributes. It provides scholarly and useful guidance on implementing AI-driven HRM in developing countries.

Originality/value: This study offers new insights for implementing AI-driven HRM in underdeveloped economies by incorporating technology readiness as a moderator and trust as a mediator between AI-enabled HRM practices and employee sustainable performance.

Keywords: AI-enabled HRM, Employee Sustainable Performance, Trust in AI, Technology Readiness, PLS-SEM, Pakistan

1| INTRODUCTION

The role of AI in HRM has changed the landscape of how modern businesses operate. Talent acquisition, talent retention, performance predictability, and learning and development are new business functions, enabled by talent-based data and AI (Tambe et al., 2019; Strohmeier and Piazza, 2024). AI has disrupted recruitment, performance management, learning and development, compensation, and satisfaction functions in modern organizations (Cavanagh et al., 2023; Bondarouk and Brewster, 2016). Beyond automation, the use of AI in HRM has far greater implications for an organization. AI has the capacity to fundamentally alter an organization's approach to managing its talent and supporting their growth in an increasingly competitive and dynamic marketplace.

While the emergence of the use of AI in HRM and the implications this may have on employee sustainable performance is a developing area of research, there is still a clear lack of scholarly material in this area (Martin et al., 2024; Taminiau et al., 2024). Employee sustainable performance refers to employees' ability to exhibit both high levels of adaptability and engagement as well as a sense of emotional and physical well-being, whilst maintaining high levels of overall productivity, and both helping to achieve the success of the organization for which they work, as well as contributing to society (Chang et al., 2018; Elkington, 1997). While it is clear that AI in HRM has the potential to optimize work processes and reduce monotonous tasks (Knott et al., 2024; Vinogradov et al., 2024), we still do not fully understand the implications of AI in HRM on employee sustainable performance, particularly psychologically. The authors would like to research the impact of employee sustainable performance by AI trust as a psychological mediator, in combination with technology readiness as a contextual factor.

In the context of Human Resource Management (HRM), employees developing trust in AI-based systems for functions such as hiring, performance reviews, promotions, and salary decisions is critical for creating a positive feedback AI-HRM framework toward sustainable performance. Trust in AI captures the extent to which employees believe a system is reliable, dependable, transparent, and acting in their best interest (Wei and Fonti, 2023; Li and Zhou, 2025). Employees who trust AI-based HRM systems will interact with the systems, accept the provided recommendations, and also be prepared to amend their behavior and practices to sustain performance.

As an additional construct, technology readiness describes someone's tendency to deal with and embrace recently available technology (Parasuraman, 2000). In AI-based HRM, this includes being optimistic, innovate, and willing to accept change, and at the same time, capturing the disgruntled, anxious, and overall negative and angry feelings toward change (Wang and Sun, 2010; Yang et al., 2013). Compared to other research streams, technology readiness is still underdeveloped and is particularly undefined for less developed countries such as Pakistan. High levels of citizen engagement and an AI-technology based state underscore its importance for future research in this area (Raza et al., 2024; Shahzad et al., 2025).

Inspired by the gaps in the existing literature, this study advances and empirically tests a theory integrating AI-based HRM, trust in AI, technology readiness, and sustainable performance of employees. Based on the unified theory of the acceptance and use of technology (UTAUT) (Venkatesh et al., 2003), social exchange theory (Blau, 1964), and technology readiness theory (Parasuraman, 2000), three hypotheses have been formulated. The first hypothesis proposes that that the use of AI in HRM would positively impact employee sustainable performance. The second hypothesis proposes that the relationship would be mediated by trust in AI. The third hypothesis proposes that the relationship would be moderated by technology readiness. By empirically testing these relationships using PLS-SEM with data collected from 310 employees across diverse industries in Pakistan, this research aims to make a meaningful contribution to both the HRM and information systems literatures, providing actionable insights for organisational leaders and policymakers seeking to harness the potential of AI in human resource processes.

2 | Literature Review

2.1AI-Enabled HRM Practices and Employee Sustainable Performance

The last few years have seen AI-centric Human Resource Management Practices (HRM) attract a lot of interest within academia as well as the industry, due to the rapidly expanding use of AI in all facets of Human Resources Management (Cavanagh et al., 2023; Strohmeier and Piazza, 2024). AI-centric HRM Practices involve the integration of several kinds of Artificial Intelligence technologies, such as machine learning, natural language processing, RPA, predictive analytics, and intelligent chatbots, that assist, automate, and enhance traditional HR Management activities, such as recruiting, training, assessment, development, reward, and engagement of employees (Knott et al., 2024; Tambe et al., 2019). These practices provide innovative opportunities to engage in different forms of HRM, beyond the existing traditions of HRM, through contextual and real-time interventions, that enhance both the effectiveness of the organization and the quality of the employee experiences(Meijerink and Boons, 2021; Taminiau et al., 2024).

An employee's sustainable performance conveys the employee's ability to consistently uphold and enhance their performance in regards to task performance, context performance, adaptability, and reduction of counterproductive behavior, across numerous time dimensions (Chang et al., 2018). Sustainable performance of employees is not just about achieving short-term performance goals of an organization. It is also speaking to an employee's ability to adjust to the various demands of an organization over the long haul, learn new skills, and sustain their physical and mental wellness to support the progress of the organizations and society at large (Elkington, 1997). The theoretical basis of AI-supported HRM technologies and their impact on employee sustainable performance is grounded in the resource-based view (RBV) of the firm (Barney, 1991). The resource-based view of the firm captures the idea that organizations that effectively and uniquely integrate valuable and difficult to replicate resources (including AI-empowered HRM) can obtain superior performance of their human capital and subsequent sustained competitive advantages.

Evidence regarding AI-enabled HRM practices and the consequences of employee performance is beginning to emerge, but is still limited. Hmoud and Laszlo (2019) and Meijerink and Boons (2021) have shown that the use of AI in HRM processes can improve the accuracy and fairness of performance appraisals, reduce inherent biases in the recruitment process, and develop personalized career paths, all of which lead to better employee outcomes. More recently, Martin et al. (2024) and Vinogradov et al. (2024) have added to the literature and shown that AI-based HRM analytics can identify employee turnover and skill gaps, and recommend measures to sustain employee performance. In Pakistan, where organizations are rapidly adopting AI in the HRM functions (Raza et al., 2024), assessing the impact of these tendencies on the development of sustainable employee performance is both timely and applicable. Based on the arguments and evidence presented above, the following hypothesis is proposed:

H1: AI-enabled HRM practices have a significant positive effect on employee sustainable performance.

2.2 Technology Readiness as a Moderator

Technology readiness, a concept originally developed by Parasuraman (2000), refers to an individual's predisposition to adopt and use new technologies, encompassing both positive enablers (optimism and innovativeness) and negative inhibitors (discomfort and insecurity) that collectively shape an individual's overall readiness to embrace technological innovations (Wang and Sun, 2010; Yang et al., 2013). In the context of AI-enabled HRM practices, technology readiness represents a potentially salient boundary condition that may influence the strength and direction of the relationship between AI-enabled HRM practices and employee sustainable performance. Employees with high technology readiness are generally more optimistic about the potential benefits of new technologies, more innovative in their approach to technology use, less discomforted by technological complexity, and less insecure about the reliability of automated systems (Parasuraman, 2000; Parasuraman and Colby, 2015).

The theoretical rationale for the moderating role of technology readiness draws upon the technology acceptance model (Davis, 1989) and the concept of individual differences in technology adoption. According to these frameworks, the impact of any technology-based organisational intervention on employee outcomes is contingent upon the individual characteristics of the technology users (Venkatesh et al., 2003). In the specific context of AI-enabled HRM practices, employees with higher levels of technology readiness may be more receptive to AI-driven changes in HRM processes, more willing to experiment with AI tools, and more capable of extracting value from AI-generated insights and recommendations (Raza et al., 2024; Shahzad et al., 2025). Conversely, employees with lower technology readiness may experience greater anxiety, resistance, or scepticism when confronted with AI-driven HRM practices, potentially attenuating the positive effects of these practices on sustainable performance.

However, an alternative perspective suggests that the moderating effect of technology readiness may be less pronounced in organisational contexts where AI-enabled HRM practices are implemented as standardised organisational systems rather than optional individual tools. When AI-driven HRM systems are embedded in organisational workflows as mandatory or normative practices, the influence of individual technology readiness on the relationship between AI-HRM practices and performance outcomes may be diminished, as all employees, regardless of their personal technology predispositions, are required to interact with these systems as part of their job roles (Marangunić and Granić, 2015). This perspective is particularly relevant in the Pakistani organisational context, where AI adoption in HRM is still in its nascent stages and organisational mandates may override individual technology readiness differences. Given these competing theoretical perspectives, the following hypothesis is proposed to empirically test the moderating role of technology readiness:

H2: Technology readiness significantly moderates the relationship between AI-enabled HRM

2.3 Trust in AI as a Mediator

Trust in AI has emerged as a central construct in the scholarly discourse on human-AI interaction, reflecting the growing recognition that the effectiveness of AI systems in organisational settings is not solely determined by their technical capabilities but is also fundamentally shaped by the psychological perceptions and attitudes of the humans who interact with them (Wei and Fonti, 2023; Glikson and Woolley, 2024). Trust in AI, in the context of HRM, refers to the willingness of employees to be vulnerable to the actions of AI-driven systems based on positive expectations about the AI's reliability, competence, benevolence, transparency, and predictability in making HR-related decisions that affect employees' careers, development, and well-being (Li and Zhou, 2025; Lankton et al., 2015). This conceptualisation draws from established trust theories in organisational behaviour

(Mayer et al., 1995) and extends them to the domain of algorithmic decision-making in HRM contexts The mediating role that trust in AI plays in the relationship between AI-enabled HRM practices and employee sustainable performance is grounded in social exchange theory (Blau, 1964) and the technology acceptance literature. Based on social exchange theory, employees develop sufficient trust in AI-enabled HRM Practices that are designed to be fair and transparent, and thus, motivate them to reciprocate by performing at a higher level, engaging, and remaining committed (Cropanzano and Mitchell, 2005). In the context of technology acceptance, the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) indicates trust has a role in determining both the subjective perception of effort and performance associated with the use of AI-based tools in HRM and thus impacts employee performance.

The psychological mechanism underlying trust in AI as a mediator can be described as follows: when organizations employ AI in HRM, employees often exhibit a range of cognitive and emotional responses to the AI. AI systems which employees perceive to be reliable and unbiased, and as aids to their professional development, lead employees to develop trust in such systems (Wei and Fonti, 2023; Colombo et al., 2024). Trust in these systems lowers employees' resistance to AI-based HRM, fosters openness to AI-based feedback and suggestions, and leads to an overall feeling of safety with which employees can use the AI systems in order to try new ways of working. AI-based HRM systems which employees trust allow them to work at an elevated performance level for prolonged periods of time. AI-based HRM has the potential for continual improvement of employees' individual performance and career development. Trust, therefore, is the psychologically important step-function that converts AI-based HRM to sustainable improved performance of employees. Recent studies like Li and Zhou (2025) and Jiang et al. (2024) have added empirically to this mechanism. Based on this the following hypothesis is proposed:

H3: Trust in AI significantly mediates the relationship between AI-enabled HRM practices and employee sustainable performance.

2.4 Conceptual Framework

The conceptual framework of this study integrates four key constructs: AI-enabled HRM practices (independent variable), employee sustainable performance (dependent variable), trust in AI (mediator), and technology readiness (moderator). The framework posits that AI-enabled HRM practices directly influence employee sustainable performance (H1), with trust in AI serving as a psychological mediator that partially transmits the effect of AI-enabled HRM practices on sustainable performance (H3). Additionally, technology readiness is proposed as a moderator that may strengthen or weaken the direct relationship between AI-enabled HRM practices and employee sustainable performance (H2). The framework is grounded in the UTAUT, social exchange theory, and technology readiness theory, providing a comprehensive theoretical lens through which the complex interplay of technological, psychological, and individual difference factors in AI-enabled HRM contexts can be examined.

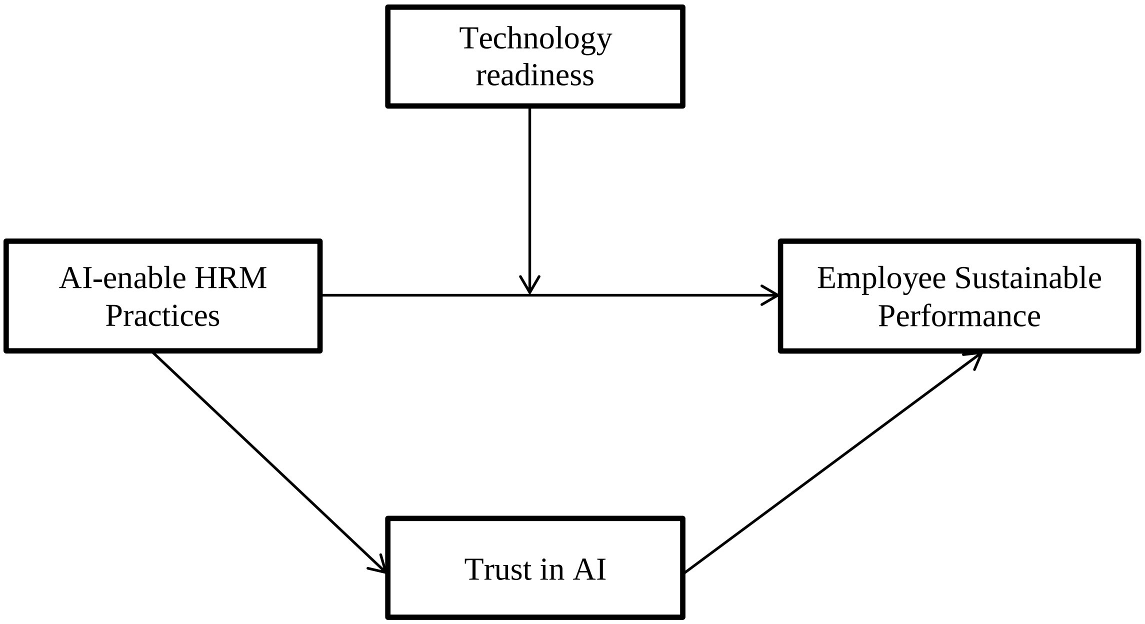

Figure-1. Conceptual Model: AI-Enabled HRM Practices, Trust in AI, Technology Readiness, and Employee Sustainable Performance

3 | Research Methodology Research Design and Sample

This study adopted a quantitative, cross-sectional research design to empirically examine the hypothesized relationships among AI-enabled HRM practices, trust in AI, technology readiness, and employee sustainable performance. The target population for this research comprised employees working in organizations across Pakistan that have adopted or are in the process of adopting AI-driven HRM technologies. A structured survey questionnaire was developed as the primary data collection instrument, drawing upon validated measurement scales from the existing literature. The survey instrument was designed using a seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree), to capture respondents' perceptions and experiences across all study constructs.

Measurement items for AI-based HRM practices were adapted from Cavanagh et al. (2023) and consist of eight items that capture the use of AI technologies in a variety of HRM functions. An assessment of employee sustainable performance was based on a ten-item scale adapted from Chang et al. (2018) and evaluated the different dimensions of sustained employee performance. Three items measuring trust in AI and adapted from Wei & Fonti (2023) and Li & Zhou (2025) include AI system reliability, benevolence, and transparency. The twelve items measuring technology readiness were adapted from Wang & Sun (2010) and Yang et al. (2013) and include both the positive and negative sides of technology predisposition. The questionnaire was pre-tested through a pilot study with a small representative sample of practitioners and academics to assess the clarity and relevance and to adjust the items for the Pakistani context of HR management.

Data were collected using either online or paper-based surveys from 310 participants covering multiple sectors of the economy including medical and healthcare, technology, finance, manufacturing, supply chain, and more. Participants were drawn from both the public and private sectors and included employees at various management level including low, middle, and high level management with different professional experience. The sample demographic had been designed to include the range of work environments to improve the broad scope of interpreting the results. Before analysis, the data was checked for incomplete answers, outliers, and conformity to the norm. Due to the nature of the research, it was decided that the best approach would be to use.

4 |Results and Discussion

4.1 Reliability Analysis

This study used Cronbach's alpha to evaluate primary study constructs and determine internal consistency and reliability of measurement instruments (Cronbach, 1951). In accordance with the criteria set by Hair et al. (2019), and Nunnally (1978), a Cronbach's alpha score of 0.70 is generally accepted as the lower limit of the reliability of a scale used in a social science research context. The constructs of AI-enabled HRM Practices (α = 0.807, n = 5) and Employee Sustainable Performance (α = 0.876, n = 3) have been shown to have high levels of internal consistency, and have been found to be well above the required level of reliability. Constructs of Trust in AI (α = 0.607, n = 3) and Technology Readiness (α = 0.528, n = 3) have been found to be below the 0.70 benchmark. While these values are considerably lower than the norm, Robinson et al. (1991) and Hinton et al. (2014) claim that in exploratory research and research based on discontinuous psychological1 constructs an alpha range of this nature may be acceptable. In the case of Technology Readiness, the lower alpha might be attributable to the "gestalt" nature of the construct, which combines motivators and inhibitors (Parasuraman, 2000). Therefore, all measurement instruments were kept to ensure integrity of the research model (Sekaran and Bougie, 2016).

Table 1

Construct/Variable	Cronbach's Alpha	No. of Items
AI-enabled HRM Practices	0.807	5
Employee Sustainable Performance	0.876	3
Trust in AI	0.607	3

Note: Cronbach's alpha threshold ≥ 0.70 (Hair et al., 2019).

4.2 Measurement Model Assessment

The evaluation of the measurement model utilised the Partial Least Squares (PLS) algorithm to assess the validity and reliability of the research constructs, focusing on individual item reliability, composite reliability (CR), and convergent validity as presented in Table 4.3.

According to Hair et al, (2019), individual item reliability is achieved when outer loadings are above the 0.708 benchmark. However, loadings between 0.40 and 0.70 may be retained if they do not adversely affect the overall reliability and convergent validity of the construct. In this study, items such as TR1 (0.490) and AIHRM5 (0.515) exhibited lower loadings but were retained to maintain content validity. Most items, including ESP6 (0.917) and AIHRM7 (0.912), demonstrated high reliability. Composite Reliability (CR) values ranged from 0.758 to 0.924, all exceeding the 0.70 criterion established by Nunnally and Bernstein (1994), supporting adequate internal consistency of all latent variables. Additionally, convergent validity was confirmed through Average Variance Extracted

(AVE), with all constructs exceeding the 0.50 benchmark set by Fornell and Larcker (1981), demonstrating that AI-enabled HRM practices (0.572), Employee Sustainable Performance (0.802), Technology Readiness (0.522), and Trust in AI (0.530) explained more than 50 percent of their respective indicators' variance.

Table 2

Variable	Items	Item Loading	CR	AVE
AI-enabled HRM Practices	AIHRM3	0.814	0.864	0.572
	AIHRM5	0.515		
	AIHRM6	0.544		
	AIHRM7	0.912		
	AIHRM8	0.896		
Employee Sustainable Performance	ESP10	0.874	0.924	0.802
	ESP2	0.895		
	ESP6	0.917		
Technology Readiness	TR1	0.49	0.758	0.522
	TR11	0.852		
	TR12	0.775		
Trust in AI	TrusAI1	0.536	0.765	0.53
	TrusAI2	0.883		
	TrusAI3	0.724		

Note: CR = Composite Reliability; AVE = Average Variance Extracted. Loading threshold ≥ 0.708; CR ≥ 0.70; AVE ≥ 0.50.

4.2 Discriminant Validity Using HTMT Ratio

another and whether the same item can measure more than one latent variable (Henseler et al., 2015). This study evaluated discriminant validity using three approaches: the Fornell-Larcker criterion (FLC), the Heterotrait-Monotrait (HTMT) ratio, and cross-loadings analysis. The HTMT ratio results are presented in Table 4.4. According to Henseler et al. (2015, 2016), HTMT values below 0.85 (a more conservative approach) or 0.90 (a more liberal approach) indicate sufficient discriminant validity. Overall, the relationships are below the more conservative HTMT threshold of 0.85, confirming that discriminant validity is achieved. However, the relatively high value of 0.749 between AIHRM and Trust in AI suggests some overlap between the two constructs, which is theoretically expected given that AI-enabled HRM practices and trust in AI are conceptually related.

Table 3 *Heterotrait-Monotrait Ratio.*

	AIHRM	ESP	TR	Trust AI
AIHRM				

ESP	0.684		
TR	0.652	0.463	
TrusAI	0.749	0.606	0.702

Note: HTMT = Heterotrait-Monotrait Ratio. Threshold < 0.85 (conservative) or < 0.90 (liberal).

4.3 Discriminant Validity Using Fornell-Larcker Criterion

Discriminant validity was further evaluated using the Fornell–Larcker criterion, as shown in Table 4.5. The criterion requires that the square root of the AVE for each construct should be greater than the correlation between that construct and any other construct in the model. The results confirm that discriminant validity requirements are met: the square root of the AVE for each construct (shown in bold on the diagonal) exceeds all inter-construct correlations. For instance, the square root of AVE for Employee Sustainable Performance (0.895) was greater than its correlations with AI-enabled HRM Practices (0.623), Technology Readiness (0.323), and Trust in AI (0.517). Similar results were found for all constructs, demonstrating that AI-enabled HRM Practices, Employee Sustainable Performance, Technology Readiness, and Trust in AI are conceptually distinct from one another.

Table 4

	AIHRM	ESP	TR	TrusAI
AIHRM	0.756			
ESP	0.623	0.895		
TR	0.474	0.323	0.723	
TrusAI	0.629	0.517	0.43	0.728

Note: Diagonal values (bold) represent the square root of AVE. Off-diagonal values represent inter-construct correlations.

4.4 Discriminant Validity Using Cross-Loadings

Discriminant validity was additionally assessed through cross-loading analysis, as presented in Table 4.6. The results indicate that items for AI-enabled HRM Practices, Employee Sustainable Performance, and Trust in AI loaded primarily on their intended constructs and exhibited lower

on their construct, while TR1 demonstrated a weaker association. Similarly, Trust in AI item TrusAI1 loaded weaker than TrusAI2 and TrusAI3. The remaining items exhibited an optimal pattern, confirming the uniqueness of the constructs and supporting the discriminant validity of the model. These results, taken together with the Fornell-Larcker criterion and HTMT ratio findings, provide robust evidence for the validity of the measurement model.

Table 4.6.

Item	AIHRM	ESP	TR	TrusAI
AIHRM3	0.814	0.554	0.365	0.496
AIHRM5	0.515	0.168	0.157	0.251
AIHRM6	0.544	0.261	0.171	0.343
AIHRM7	0.912	0.578	0.502	0.579
AIHRM8	0.896	0.602	0.449	0.596
ESP10	0.542	0.874	0.277	0.471

ESP2	0.555	0.895	0.272	0.424
ESP6	0.577	0.917	0.317	0.493
TR1	0.199	0.148	0.49	0.21
TR11	0.366	0.28	0.852	0.337
TR12	0.429	0.252	0.775	0.366
TrusAI1	0.209	0.159	0.183	0.536
TrusAI2	0.653	0.532	0.392	0.883
TrusAI3	0.349	0.305	0.314	0.724

Note: Bold values represent loadings on the intended construct. Cross-loadings should be lower than the primary loading.

4.5 Structural Model and Hypothesis Testing

A structural model in PLS-SEM tests the hypothesised relationships between latent constructs using direct effects, specific indirect effects, and moderation effects, with t-statistics and p-values to assess the model's explanatory and predictive capabilities (Hair et al., 2012). The results of hypothesis testing using PLS bootstrapping with 5,000 resamples are presented in Table 4.8. Three hypotheses were tested, examining the direct effect of AI-enabled HRM practices on employee sustainable performance (H1), the moderating effect of technology readiness on this relationship (H2), and the mediating effect of trust in AI (H3).

Table 4.8

Hypothesis	Std. Beta	Std. Error	t-value	p-value	Decision
H1: AIHRM → ESP	0.498	0.055	9.11	0	Accepted
H2: TR × AIHRM → ESP	(−0.025)	0.044	0.56	0.575	Rejected
H3: AIHRM → TrusAI → ESP	0.134	0.038	3.481	0.001	Accepted

Note: AIHRM = AI-Enabled HRM Practices; ESP = Employee Sustainable Performance; TR = Technology Readiness; TrusAI = Trust in AI; β = Standardized Beta; SE = Standard Error.

4.6 Direct Effect and Moderation

performance ($\beta = 0.498$, $SE = 0.055$, $t = 9.110$, $p = 0.000$). The t-value, far exceeding the 1.96 benchmark, coupled with a p-value of 0.000, indicates a high level of statistical significance that satisfies the requirement of $p < 0.001$ (Hair et al., 2019). Therefore, H1 is substantiated, positing that AI-integrated HRM practices significantly influence employee sustainable performance across various industries in Pakistan. This finding aligns with the UTAUT framework (Venkatesh et al., 2003) and the studies of Hmoud and Laszlo (2019) and Meijerink and Boons (2021), confirming that AI integration in HRM processes enhances sustained employee performance.

H2: Technology Readiness × AI-Enabled HRM Practices → Employee Sustainable Performance. The interaction between technology readiness and AI-enabled HRM practices produces a non-significant outcome ($\beta = -0.025$, $SE = 0.044$, $t = 0.560$, $p = 0.575$). With a t-value of 0.560, which is well below the critical threshold of 1.96, and a p-value of 0.575, which exceeds the 0.05 significance level, it is concluded that technology readiness does not serve as a significant moderator in the relationship between AI-enabled HRM practices and employee sustainable performance (Hair et al., 2019). The beta coefficient of -0.025 is very small, confirming the absence of any moderation effect of practical importance (Cohen, 1988). Thus, H2 is rejected, indicating that in the cross-industry workforce of Pakistan, the performance-enabling effect of AI-enabled HRM practices is similar across employees regardless of their levels of technology readiness.

4.7 Mediating Effect

H3: AI-Enabled HRM Practices → Trust in AI → Employee Sustainable Performance. The bootstrapped indirect effects analysis supports the mediating role of trust in AI on the relationship between AI-integrated HRM practices and employee sustainable performance ($\beta = 0.134$, $SE = 0.038$, $t = 3.481$, $p = 0.001$). The bias-adjusted confidence interval ($LL = 0.056$, $UL = 0.209$) provides strong statistical evidence of mediation at the $p < 0.01$ level, as the interval does not contain zero (Hair et al., 2019; Preacher and Hayes, 2008). Therefore, H3 is supported, indicating that trust in AI serves as a significant partial psychological mediator of the effect that AI-enabled HRM practices have on sustainable employee performance. This finding underscores the theoretical importance of considering employee trust as a psychological pathway through which AI-driven HRM systems influence performance outcomes.

4.8 Summary of Hypotheses Testing

In summary, the empirical analyses conducted in this research provide a solid foundation for two of the three principal hypotheses of the conceptual framework. The verification of Hypothesis 1 (H1) is the most remarkable outcome, illustrating the existence of a significant and positive direct association between AI-enabled HRM practices and employee sustainable performance. This suggests that the incorporation of AI tools and technologies into HRM, from the automation of recruitment processes to the application of AI for predictive analytics, may play an important role in the sustainable performance of employees and the organisation as a whole. This finding substantiates the proposition that AI should be considered a core strategic resource and a key differentiator in employee performance management (Tambe et al., 2019; Strohmeier and Piazza, 2024).

The research also substantiates Hypothesis 3 (H3), recognising trust in AI as a significant complementary partial mediator in the relationship between AI-enabled HRM practices and employee sustainable performance. This finding has theoretical value as it addresses the "black box" of the

systems depends critically on employees' perceptions of the system's trustworthiness, transparency, and alignment with their work interests (Wei and Fonti, 2023). Trust serves as the mediator, and the research illustrates that HRM technology systems should focus not only on the technical operationalization of AI but also on fostering and strategically managing employee perceptions of the AI systems employed in HRM.

On the other hand, the data did not support Hypothesis 2 (H2), which posited that technology readiness would moderate the relationship between AI-enabled HRM practices and employee sustainable performance. This finding, although statistically non-significant, provides unique insights in the cross-Sectoral context of Pakistan. It suggests that organisations do not need to limit the benefits of AI-driven HRM systems exclusively to employees who are "technology pioneers" or possess high levels of technological readiness; instead, employees with lower levels of technological predisposition can also benefit. This represents a significant opportunity for management, as organisations can introduce AI HRM systems to heterogeneous employee groups without fear that employees with low technological readiness would not achieve sustainable performance thresholds. The results imply that a trust-centred, well-constructed AI-HRM system would have a higher-order effect compared to the technological discomfort or insecurity of employees.

Explanatory Power

The coefficient of determination (R^2) evaluates the model's explanatory power by measuring the extent to which predictor constructs explain the variance of the endogenous constructs (Hair et al., 2019; Chin, 1998). The R^2 for Employee Sustainable Performance is 0.415, with an adjusted R^2 of 0.407, indicating that the predictor constructs—AI-enabled HRM practices, trust in AI, and the technology readiness interaction term—account for 41.5% of the total variance in employee sustainable performance. The adjusted R^2 of 0.407 demonstrates that the variance explained is not attributable to model over-parameterization and that the predictor constructs explain the variance in employee sustainable performance in a meaningful and substantial manner. For Trust in AI, R^2 is 0.395, with an adjusted R^2 of 0.393, demonstrating that AI-enabled HRM practices, as the sole predictor, explains 39.5% of the variance in employee trust in AI.

Table 4.10.

Construct	R^2	R^2 Adjusted
Employee Sustainable Performance	0.415	0.407
Trust in AI	0.395	0.393

Note: R^2 = Coefficient of Determination.

This study makes useful theoretical and practical contributions to the existing literature on AI use in HRM and its impacts on employee sustainable performance. The main finding from this study is that AI use in HRM has a direct, positive, and significant effect on employee sustainable performance ($\beta = 0.498$, $p < 0.001$). This finding confirms expectations from the resource-based view (Barney, 1991) and the UTAUT model (Venkatesh et al., 2003). Together, these theories suggest that an organization's use of AI in HRM is a valuable resource that improves employee outcomes. The effect is high due to the substantial role AI-centered HRM can play in employee sustainable performance. This finding supports recent studies by Martin et al., (2024) Knott et al. (2024) and Vinogradov et al. (2024) who have employed AI in HRM and recorded improved employee performance, engagement, and retention. The main recommendation for Pakistani organizations is to invest in AI across all HRM functions to enhance employee sustainable performance, including recruitment, selection, performance management and HRM functions of training and development.

The second key finding is the significant role of trust in AI as a mediator in the relationship between AI-based HRM practices and sustainable performance of employees ($\beta = 0.134$, $p < 0.01$). This finding demonstrates the trust in AI mediating sustainable performance of employees through the AI-based HRM practices from an existing theory namely the social exchange theory (Blau, 1964) and extends the existing literature. Partial mediation supports the notion that AI-based HRM practices enhance sustainable performance of employees, but trust in AI systems is one of the mechanisms. This finding is crucial in Pakistan, considering employees' trust in AI-based practices and the country's cultural attitude toward AI, along with job displacement and digital divide issues (Raza et al., 2024; Shahzad et al., 2025). If organizations wish to optimize the performance of AI-based HRM practices, a trust-building approach employing an AI interface must be incorporated along with the necessary technology. The findings are in agreement with Wei and Fonti (2023), Li and Zhou (2025), and Glikson and Woolley (2024). They focus on the most important factor for the success of AI deployment in organizations which is employee trust.

The third finding, the non-significant moderating effect of technology readiness ($\beta = -0.025$, $p > 0.05$), is both surprising and somewhat informative. Technology readiness theory (Parasuraman, 2000) and previous empirical studies (Wang and Sun, 2010; Yang et al., 2013) proposed that technology predisposition will moderate the impact of technology-based organizational interventions. In contrast, this study's findings show that in the Pakistani context, technology-based AI tools in HRM do not need technology readiness predisposition. There are many possible ways to interpret this non-finding. First, it could be that when AI-based tools in HRM are automatically used within the organizational system, then the difference in the readiness level to use technology is of lesser importance. Second, it could be that, within the context of organizations in Pakistan, the organizational support, training, and change management employed with AI-HRM has addressed some of the issues related to technology readiness. Third, it could be that in the context of Pakistani HRM, AI is at a relatively early stage of implementation, and workers of all levels of readiness to use technology are likely impacted by the introduction of AI tools in HRM within the organization. This finding has a positive implication for practice in that organizations will not need to consider their employee's level of technology readiness when using AI-based tools in HRM because of the positive effect AI will have on HRM.

5 | Conclusion and Recommendations

This study set out to investigate the influence of AI-enabled HRM practices on employee sustainable performance, with a particular focus on the mediating role of trust in AI and the moderating role of technology readiness. Drawing upon data from 310 employees across diverse industries in Pakistan and employing PLS-SEM as the analytical technique, the study yielded three principal findings. First, AI-enabled HRM practices have a significant and positive direct effect on employee sustainable performance, confirming that the integration of AI technologies into HRM functions enhances the sustained performance of employees. Second, trust in AI significantly mediates this relationship, revealing that a portion of the performance-enhancing effect of AI-enabled HRM practices operates through the psychological mechanism of employee trust. Third, technology readiness does not significantly moderate the direct relationship between AI-enabled HRM practices and employee sustainable performance, suggesting that the performance benefits of AI-HRM practices are accessible to employees regardless of their technological predispositions.

It is recommended that future studies include boundary conditions and moderators such as consumer tech literacy, age-group-based segments and varying degrees of product involvement to determine the varying importance of AI images and/or the issue of authenticity. Additionally, Media Richness Theory-based alternative pathways that consider content quality, cognitive engagement and interaction with the video may better illuminate the video-trust pathway. A variety of cross-industry studies that include both high (e.g. financial, medical) and low threat marketplaces (e.g. fast fashion) are warranted along with experimental and longitudinal studies that incorporate behavioral-based trust measures. the study finds that AI videos are more effective than still AI images in mitigating the perceived risk among consumers, decreasing consumer skepticism, and building trust. While still images generated by AI are increasingly criticized and negatively perceived, videos generated by AI are viewed less skeptically and more positively. The study also takes issue with the marketing assumption that consumers are looking for genuine, unedited content. In fact, synthetic videos that are aesthetically pleasing and do not increase trust of consumers are viewed positively. Rather, trust of consumers is rooted in the perceived safety of the transaction and the service and media used. This suggests that, especially with the growing use of AI, trust is built from the integration of transparency and the depth of information, as compared to the overt priority of the visual accuracy of the content.

6 |IMPLICATIONS

6.1 Theoretical Implications

Theoretically, this study adds three important contributions. First, this study extends the scholarship of AI-HRM by offering the first empirical evidence of the direct relationship between AI-enabled HRM practices and employee sustainable performance in a developing economy, where similar studies are absent (Strohmeier and Piazza, 2024; Taminiau et al., 2024). Most of the previous studies have focused on the adoption of AI in HRM in developed economies. This study demonstrates that the performance enhancing effects of AI-enabled HRM practices are present in Pakistan, thus extending the AI-HRM literature beyond borders. Second, the current study is the first to address trust in AI as a significant mediator, therefore explaining and integrating social exchange theory (Blau 1964) and the technology acceptance model (Venkatesh et al. 2003) in a unique perspective. Third, the absence of a moderating effect of the gap between technology readiness and the existence of the current dominant technology assumes that in the adoption of AI by organizations, means and strategies adopted by the organizations are of primary importance, and are likely to be of greater significance than individual differences.

6.2 Practical Implications

This research has several recommendations for organizational managers, HR managers, and technology vendors. First, results show that the AI-enabled HRM systems have considerable benefits to employee performance, which makes AI technology worthwhile across all the HRM functions. Thus, with the expectation of long-term improvements from the performance management, recruitment, learning and development, and engagement of employees, organizations should use AI tools. Second, the results show that trust in AI has a mediating effect. This means managers need to implement strategies that improve employee trust in the AI HRM systems. This could be done by the organization communicating to employees how AI plays a role in making decisions in the HR domain, integrating employees in the design of AI systems used for HR, and ensuring adequate support and training of the employees, and setting up an accountability mechanism with a clear grievance process for the AI-based decisions (Wei and Fonti, 2023). Third, having a non-significant effect on technology readiness means that the benefits of AI-powered HRM are likely to be enjoyed by the staff within the organization, regardless of the level of technology readiness of the staff, and organizations need not engage in comprehensive technology readiness assessments, as long as basic level training is done for staff.

6.3 Limitations

Several limitations of the current study exist which also provide research opportunities. First, the cross-sectional nature of the study means causality cannot be determined, and longitudinal studies can address this by looking at the ordering of variables in time and causal relationships. Second, the nature of self-reported perceptual data can lead to common method bias, and future research can integrate objective performance metrics, multi-source evaluations, and/or research designs. Third, the study was done in Pakistan, and the results cannot be easily generalized to other cultures, institutions, and/or economies. Cross-national studies would help overcome these limits. Fourth, the current study focuses on a few mediators and moderators, and future research can look at additional psychological constructs like the AI anxiety, algorithmic transparent, and fairness perceptions as well as the boundary conditions like the organizational culture, the maturity of AI in the organization, industry, and national cultures. Fifth, the lower reliability scores of the two constructs, Trust in AI, and the Technology Readiness, call for further measurement refinement in the AI-HRM. Notwithstanding these limitations, the study makes a significant contribution to the literature by being one of the first to empirically examine the direct, mediating, and moderating paths between AI enabled HRM and employee sustainable performance.

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