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# THE IMPACT OF AI-ENABLED HRM PRACTICES ON EMPLOYEE WORK ENGAGEMENT: THE MODERATING ROLE OF EMPLOYEE DIGITAL LITERACY

**Dr. Muhammad Asif [1], Dr. Muhammad Azizullah Khan [2]**

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**Affiliations:**

[1] Preston University, Kohat, Islamabad Campus, Pakistan
Email: dr.asifmails@gmail.com
ORCID: https://orcid.org/0000-0001-6576-2805

[2] Preston University, Kohat, Islamabad Campus, Pakistan
Email: azizpakpost@yahoo.com

**Corresponding Author's Email:**

[1] dr.asifmails@gmail.com

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**Abstract**

*Integrating artificial intelligence (AI) into human resource management (HRM) has revolutionized the way companies recruit, manage, and empower their staff. The current incorporation of AI into HRM has transformed the way organizations engage, manage, and recruit their employees. As AI becomes increasingly integral to HRM, there is a debate regarding its impact on employee work engagement. Based on the Job Demands-Resources (JD-R) model and Social Exchange Theory (SET), the current study creates and tests a moderated model explaining the relationship of AI-based HRM practices with employee work engagement in the presence of the moderating variable of employee digital literacy. Data were gathered using a quantitative cross-sectional design from 412 FTEs employed in organizations that used AI-enabled HR systems in the IT, banking, and telecom services sectors in Pakistan. Partial Least Squares Structural Equation Modelling (PLS-SEM) and hierarchical regression analysis were used to test the hypotheses. The results showed that AI-assisted HRM practices have a positive and significant impact on employees' work engagement ($\beta = 0.412$; $p < 0.001$). Additionally, employee digital literacy has a significant and positive moderation effect on the relationship between AI-enabled HRM and work engagement (interaction term $\beta = 0.156$, $p < 0.01$): the positive effect of AI-enabled HRM on work engagement is more pronounced for the more digitally literate employees. The model accounts for 38.7% of the variance in work engagement. By highlighting the role of AI in HRM as a job resource that positively influences employee engagement, when employees have the digital literacy to manage it, these findings support the JD-R model. Theoretical and practical implications, limitations, and suggestions for future research are presented.*

**Keywords:** AI-Enabled HRM, Employee Work Engagement, Digital Literacy, Job Demands-Resources Model, PLS-SEM, Moderating Effect

## 1. Introduction

The world's workforce is rapidly changing as AI technologies have progressed. From recruitment and selection to performance management, training and development, and employee engagement, AI is being adopted by organizations across various industries to enhance their HRM processes. According to the forecast by the Grand View Research (2025), the global AI in HR market is estimated to grow at a CAGR of more than 23% and reach USD 12.4 billion by 2030 from USD 3.5 billion in 2024. The rise of AI technologies in HRM has sparked significant academic and practical inquiries into the implications of these innovations for the employee experience and their impact on organizational outcomes.

Employee work engagement, which is a positive, fulfilling state of mind at work involving vigor, dedication and absorption, has grown as a key driver of organizational success. According to Gallup (2024), the global cost of low employee engagement is estimated to be US $8.9 trillion per year, which is estimated to be 9% of the world's GDP. On the other hand, companies with highly engaged employees are 21% more profitable, 17% more productive and 41% less likely to experience absenteeism (Gallup, 2024). With the significant implications of employee engagement in terms of both the economy and the organization, it is not surprising that examining the impact of emerging technologies on this construct is timely and important.

The use of AI in HRM brings about a dilemma. On the one hand, AI can be used in HRM practices to improve operational efficiency, streamline administrative tasks, and generate data-driven insights that can be used for employee development. On the other hand, AI can be utilized in HRM practices for boosting operational efficiency, decreasing administrative workload and giving data-driven insights for developing employees. These practices can serve as job resources and support employees in their job performance, which can lead to increased engagement. Conversely, AI-powered HRM can also create new challenges like technostress, privacy issues, algorithmic bias, and the lack of human interaction, potentially affecting employee trust and engagement. This conflict has not been fully answered in the scholarly literature, as some studies found positive correlations between AI-supported HRM and employee engagement while others found negative correlations.

This study aims to fill this gap by using the Job Demands-Resources (JD-R) model to assess the use of AI in HRM practices. According to JD-R model, job resources like Artificial Intelligence (AI) implemented HRM practices, feedback, autonomy support and development opportunities, can motivate work engagement. The effectiveness of these resources could be dependent on the employee characteristics, specifically employees' digital literacy, which refers to their ability to effectively utilize digital tools and systems that use AI. Those who are more digitally literate might find that AI-powered HRM will be a tool that works for them, while others with less digital literacy may find it a burden.

This study is especially relevant in the context of this study. In the past few years, Pakistan's financial and telecommunication sectors have seen significant digital transformation, as information technology is increasingly becoming a part of financial services (Asif, 2022). The post-COVID-19 economic climate also has driven more adoption of digital tools and AI systems within organizations (Asif et al., 2022). In an emerging economy with diverse levels of digital literacy, these areas offer a compelling context for the study of the effects of AI on employee engagement in HRM.

The research in this paper has three main contributions to the literature. First, it expands the JD-R model by proposing a multi-dimensional concept of AI-enabled HRM practices and empirically testing this construct with work engagement. Second, it takes employee digital literacy as a boundary condition which affects the relationship between AI enabled HRM and engagement, thus resolving the mixed findings in the literature. Third, it offers practical guidance for HR professionals aiming to maximize the HR engagement benefits of AI investments while minimizing potential risks.

The paper is organized as follows: Literature Review and the development of theoretical framework and hypotheses are presented in Section 2. The research methodology such as sampling, procedure of measurement and analytical is described in Section 3. The findings of the statistical analyses are presented in Section 4. The results of the study are examined in light of theory and practice in Section 5. The limitations and directions for future research are presented at the end of section 6.

## 2. Literature Review and Theoretical Framework

### *2.1 AI-Enabled HRM Practices*

AI powered HRM practices are the implementation of AI technologies like machine learning, natural language processing, predictive analysis and robotic process automation in HRM processes. These practices cover the entire employee lifecycle - from hiring to onboarding, performance management, learning and development, and offboarding. AI systems are used in recruitment and selection to scan resumes, perform preliminary candidate evaluations with chatbots, and forecast job compatibility based on past data. In recruitment and selection, AI systems are used to scan resumes, perform preliminary candidate evaluations with the help of a chatbot, and predict job fit based on past data. Within the context of performance management, AI-driven tools can offer immediate feedback, track performance patterns, and suggest growth interventions. In the field of learning and development, AI systems can tailor learning materials to the unique learning styles and skill gaps of each student. AI sentiment analysis and pulse surveys are used to track employee morale in employee engagement, offering actionable insights.

Several aspects of AI-enabled HRM practices are mentioned in the literature. Prikshat et al. (2023) created an eight item scale to measure the extent of the use of AI in HRM functions such as recruitment, training and development, performance management, and talent management. There has also been a handful of other studies that have examined specific applications, like artificial intelligence technologies for feedback systems and AI for HR analytics. In this research, AI based HRM practices are defined as a multi-dimensional construct comprising of AI for recruitment and selection, AI for training and development, AI for performance management, and AI for employee engagement.

Leadership and digital transformation skills (Aurangzeb & Asif, 2021) are critical to the successful adoption of AI in HRM. Moreover, HR professionals' administrative skills are vital in influencing job performance and employee outcomes (Aurangzeb et al., 2021). This indicates that having AI tools is not enough; the management and support of these tools by HR professionals are equally critical for their effectiveness.

### *2.2 Employee Work Engagement*

According to Schaufeli et al. (2006), work engagement is a positive, fulfilling, work-related state of mind, as it is marked by vigor, dedication and absorption. Vigor is having a lot of energy, mental strength while working, willingness to invest effort in work and persistence in the presence of difficulties. Dedication is an attitude of significance, enthusiasm, inspiration, pride and challenge in regard to work. Absorption - complete focus and being absorbed in one's work, where time seems to fly and detachment is hard to come by.

The Utrecht Work Engagement Scale (UWES-9) is the most prevalent instrument for measuring work engagement, which is composed of nine items that cover vigor, dedication and absorption (Schaufeli et al., 2006). The UWES-9 has shown very good psychometric properties in various cultures, with typically high internal consistency (ICC) ranging between 0.90 and above. Bakker and Demerouti (2017) have shown a consistent association between work engagement and a range of positive organizational outcomes such as job performance, organizational citizenship behaviour, customer satisfaction and decreased intention to leave the organization.

Within the Pakistani context, employee engagement has been correlated with job satisfaction, leadership qualities, and psychological capital (Asif & Shaheen, 2022; Asif et al., 2019). Engagement also tends to be contingent to conflict management, specifically in financial services (Asif, 2021). The study's results highlight the significance of individual and organizational variables in promoting engagement and offer a foundation for exploring the potential impact of using AI in HRM practices on this key construct.

### *2.3 Theoretical Framework: Job Demands-Resources Model*

The Job Demands-Resources (JD-R) model offers a comprehensive theory regarding how AI-based HRM practices affect employees' work engagement. The JD-R model suggests that there are two job dimensions, namely job demands and job resources. Job demands are the psychological, physical, social, or organizational component of the job that demands a person to exert continuous mental or physical effort and thus have a physiological or psychological cost. Job resources are physical, psychological, social or organizational characteristics of the job that function in the accomplishment of job goals, help to lower physiological and psychological costs of the jobs, or encourage personal growth, learning and development.

According to the JD-R model, two different processes are proposed: the health-impairment process and the motivational process. Chronic job demands use up employees' mental and physical resources, causing job burnout or health issues in the health impairment process. In the motivational process, job resources play a role in work engagement in satisfying basic human needs, autonomy, competence, and relatedness. The model also suggests that job resources become more salient and have greater motivational potential when employees are faced with high job demands (Bakker & Demerouti, 2017).

The literature has found a strong link between the motivational theories and the health of the firms and their outcomes with employees (Alizai et al., 2021). The JD-R model is in line with these theoretical traditions and provides insights into why job resources are motivators and/or engagers. In the context of AI-enabled HRM, the model implies that AI-enabled HRM practices could be considered as job resources that support employee work engagement. By leveraging AI tools, HR professionals can streamline their recruitment processes, cut down on administrative tasks, and make more data-informed and objective hiring choices. AI can enhance training and development with tailored learning opportunities that meet the needs of employees for competence and growth. With the aid of AI, one could be able to give on-the-spot feedback and reward, addressing employees' requirements for competence and relatedness. Voiceless and autonomously-driven engagement programs may meet employees' needs for autonomy and relatedness by leveraging AI.

But the utility of AI-powered HRM as a job resource can depend on the employees' capacity to effectively use these resources. This is where the importance of employee digital literacy can be of great importance. Employees' ability to use digital technologies to find, evaluate, create, and communicate information is what will decide how well they can use and gain the benefit of AI-powered HRM systems. Employees who are more digitally literate are more likely to view AI-powered HRM as a tool that assists them in their work, whereas those less digitally savvy are more likely to view the same systems as burdens that take away from their resources and detract from employee engagement.

### *2.4 Employee Digital Literacy as a Moderator*

Digital literacy is the cognitive and technical ability to locate, assess, produce and share information using information and communication technologies. Digital literacy in the workplace includes the skills of using digital tools and platforms, navigating digital interfaces, interpreting data visualization, and using technology to increase productivity and learning. New frameworks, including the expanded DigComp 2.2, evaluate digital competence in terms of information and data literacy, communication and collaboration, creation of digital content, safety, and problem-solving.

Digital literacy becomes even more significant when discussing AI-powered HRM. When it comes to AI-powered HRM, employee digital literacy becomes even more pertinent. AI systems are intricate and frequently depend on the user to understand algorithmic results, navigate new user interfaces, and learn new capabilities. Staff members who have greater digital literacy are more likely to be able to work through these complexities, interpret the information they get from AI tools, and incorporate recommendations they receive from AI seamlessly into their workflows. However, workers who are less technologically adept might feel frustrated, anxious, and resistant to HRM systems that incorporate AI.

Digital technologies can have a positive impact on work engagement but can also pose risks like internet addiction and excessive technology usage that can negatively impact wellbeing (Shahid et al., 2022). That's another indication of the role of digital literacy as a protective and enabling resource. Digital literacy has been discussed in the related contexts as moderation. Zhan and Xie (2025) concluded that digital literacy would help to buffer the link between workplace digitalization and work engagement, meaning that the positive impact of digitalization on challenge appraisals would be greater for those with greater digital literacy. Likewise, Shatila et al. (2026) showed that digital literacy boosts the positive association among AI recruitment, learning and development, and employee engagement. Based on these results, this study suggests that the connection between the AI-enabled HRM practices and work engagement can be moderated by digital literacy, meaning that the impact of these practices will be more pronounced for employees who have a higher level of digital literacy.

### *2.5 Hypotheses Development*

Based on the JD-R model and the literature reviewed, the following hypotheses are suggested:

**H1:** AI-enabled HRM practices have a positive effect on employee work engagement.

This hypothesis is based on the motivational process described in the JD-R model: job resources like AI-enabled HRM practices create engagement by meeting basic human needs and allowing for goal attainment. This correlation has been supported by empirical evidence, which has shown that there are positive links between AI adoption and employee engagement. In the telecommunications industry, emotional intelligence has been recognized as a vital mediator between emotional intelligence and team performance (Asif et al., 2022). AI-powered HRM can also help to promote engagement by instilling trust and increasing the sense of support.

**H2:** Employee digital literacy positively moderates the relationship between AI-enabled HRM practices and employee work engagement.

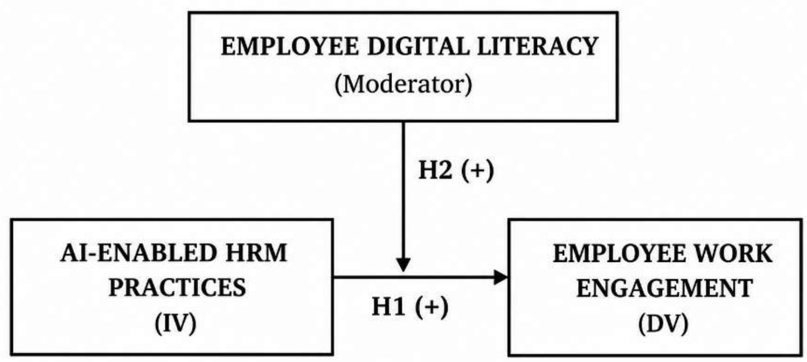
**H2a:** The positive effect of AI-enabled HRM practices on work engagement is stronger for employees with high digital literacy.

**H2b:** The positive effect of AI-enabled HRM practices on work engagement is weaker for employees with low digital literacy.

This hypothesis is supported by the proposition of the JD-R model that the motivational potential of job resources is dependent on personal resources. Digital literacy works as an employee tool that allows them to leverage AI-powered HRM resources. It is important to note that, employees with the higher level of digital literacy are more likely to think of HRM with AI as a resource, while employees with a lower score of digital literacy are more likely to think of HRM with AI as a demand.

**Figure 1**

*Conceptual Framework*




*Note.* Figure 1 is the conceptual framework of the study. The figure depicts the hypothesized relationships among AI-enabled HRM practices (independent variable), employee work engagement (dependent variable), and employee digital literacy (moderator). H1 proposes a positive direct effect of AI-enabled HRM practices on employee work engagement. H2 proposes that employee digital literacy positively moderates the relationship between AI-enabled HRM practices and employee work engagement, such that the positive effect is stronger for employees with higher digital literacy.

## 3. Methodology

### *3.1 Research Design and Sample*

The design of this research was quantitative, cross-sectional survey. The study included full-time employees in organisations with AI in HRM systems as their target population. The sample included three sectors with high usage of AI in HRM: information technology, banking, and telecommunications. The chosen sectors were chosen due to their extensive use of HRM functions involving AI technologies such as AI-assisted recruitment, performance management, training and development. These sectors were also chosen as they have shown significant digitisation and AI usage in Pakistan (Asif 2022; Asif et al 2022).

Participants were recruited using a non-probability method, convenience sampling. The sample size was calculated using the requirements for the Partial Least Squares Structural Equation Modelling (PLS-SEM). Based on Hair et al. (2022) recommendation, a minimum sample size equal to 10 times the maximum number of arrows that converge to a construct in a model was determined. The minimum sample size obtained was equal to six arrows pointing at work engagement: four dimensions of AI-enabled HRM, digital learning, and interaction term. To provide sufficient statistical power and generalizability, however, it was decided that

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a sample of 400 would be needed. A total of 412 valid questionnaires were received (at least 100 was the minimum required for PLS-SEM, and 400 was the minimum required for significant effects detection).

Most of the sample consisted of males (62.4%) and the mean age was 34.2 years (SD = 8.7). Most of the participants had a bachelor's degree (54.6%) or a master's degree (31.8%). The average number of years of work experience for the participants was 7.3 years (SD = 5.2), and the average length of time with the organization was 4.1 years (SD = 3.3). By sector, most of the respondents were employed in IT (38.6%), banking (32.5%) and telecommunications (28.9%). Table 1 shows the demographic characteristics.

**Table 1**

*Demographic Characteristics of Respondents*

| Characteristic | Category | Frequency (N) | Percentage (%) |
|---|---|---|---|
| Gender | Male | 257 | 62.4 |
| | Female | 155 | 37.6 |
| Age | 20–29 years | 142 | 34.5 |
| | 30–39 years | 178 | 43.2 |
| | 40–49 years | 71 | 17.2 |
| | 50+ years | 21 | 5.1 |
| Education | Bachelor's | 225 | 54.6 |
| | Master's | 131 | 31.8 |
| | PhD | 28 | 6.8 |
| | Other | 28 | 6.8 |
| Sector | IT | 159 | 38.6 |
| | Banking | 134 | 32.5 |
| | Telecommunications | 119 | 28.9 |

### *3.2 Measures*

**AI-Enabled HRM Practices.** An adaptation of the scale by Prikshat et al. (2023) was used to measure AI-enabled HRM practices. The instrument is made up of 8 items related to the use of AI in HRM functions. For this study, the scale was expanded with 16 items, covering the four aspects of AI-assisted recruitment and selection (4 items), AI-enabled training and development (4 items), AI-driven performance management (4 items) and AI-supported employee engagement (4 items). The examples include the following: "Our organization uses AI to screen job applicants" and "AI gives personalized training recommendations to employees." The answers were given by using a 5-point Likert scale ranging from "strongly disagree" to "strongly agree". The internal consistency of the scale was excellent (Cronbach's $\alpha = 0.934$).

**Employee Work Engagement.** The Utrecht Work Engagement Scale (UWES-9) was used to assess work engagement, a nine-item questionnaire. The UWES-9 measures three factors: vigor (3 items), dedication (3 items), absorption (3 items). Examples of questions are 'At my work I feel bursting with energy' (vigor), 'I am enthusiastic about my job' (dedication) and 'I get carried away when I am working' (absorption). The responses were marked on a scale of 0 to 6 (never, rarely, sometimes, often, very often, quite often, and always). The scale had a high level of internal consistency (Cronbach's $\alpha = 0.951$).

**Employee Digital Literacy.** Digital Literacy was assessed with a 10-item scale adapted from Kim and colleagues' (2024) Digital Literacy in the Workplace Scale (DLWS). The scale measures employees' competencies with digital tools, understanding of digital information, working collaboratively through digital platforms, and adjusting to new digital technologies. Sample items include: "I can easily learn to use new digital tools" and "I can effectively use digital platforms for collaboration." Responses were measured on a 5-point Likert Scale from 1 (strongly disagree) to 5 (strongly agree). The scale had a very high degree of internal consistency (Cronbach's $\alpha = 0.912$).

**Control Variables.** In line with the literature, the following control variables were included: Gender, Age, Education, Organizational Tenure, and Sector to control for possible confounding effects on work engagement.

### *3.3 Data Collection Procedure*

Data were gathered using an online survey using Google Forms. The survey was sent via professional networks, LinkedIn groups and organizational email lists. Anonymity and confidentiality were ensured with participants. Results of the survey are based on a survey period of six weeks from January to February 2026. There were 512 responses initially received. Of the 100 responses, 100 were dropped due to missing more than 10% from the data, straight-lining form, or lack of attention to the attention checks. There were 412 valid responses that gave a valid response rate of 80.5%.

### *3.4 Statistical Analysis*

The data were analysed using SPSS version 29 and SmartPLS version 4. Analytical procedure was conducted in two stages as suggested by Anderson and Gerbing (1988). First, the measurement model was evaluated for its reliability and validity through Confirmatory Factor Analysis (CFA) in a PLS-SEM approach. Secondly, the structural model was evaluated to examine the hypothesized relationships.

**Measurement Model Assessment.** Cronbach's alpha and composite reliability (CR) were used to test the internal consistency reliability, with a value above 0.70 being acceptable. Average Variance Extracted (AVE) was used to test convergent validity and value of 0.50 or higher was considered as acceptable. The Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio were used to assess the discriminant validity; HTMT values of less than 0.85 were judged to be acceptable.

**Structural Model Assessment.** Path coefficient, coefficient of determination ($R^2$), effect size ($f^2$) and predictive relevance ($Q^2$) were used to evaluate the structural model. The hypothesis test was carried out by applying bootstrapping method with 5000 resamples to calculate t-statistics and standard errors. The product-indicator approach was used for the moderating effect, and the interaction term was generated by multiplying the standardized scores of AI-enabled HRM practices and digital literacy.

**Hierarchical Regression Analysis.** Hierarchical regression analysis was performed to further explore the moderating effect and as a robustness check in SPSS. The control variables, as well the main effects (AI-enabled HRM practices and Digital Literacy), and the interaction term (AI-enabled HRM × Digital Literacy) were entered in three steps, respectively. This change in R2 ($\Delta$R2) was assessed to check the incremental variance explained by the interaction term.

## 4. Results

### *4.1 Measurement Model Assessment*

The measurement model was evaluated on three aspects: internal consistency reliability, convergent validity, and discriminant validity. All constructs had an internal consistency reliability (Cronbach's alpha) > 0.90 and composite reliability > 0.90 (see Table 2), which indicated excellent internal consistency reliability. The average variance extracted (AVE) ranged from 0.641 to 0.782, which is all above 0.50, considered to be satisfactory convergent validity.

**Table 2**

*Measurement Model Assessment*

| Construct | Items | Cronbach's α | CR | AVE |
|---|---|---|---|---|
| AI-Assisted Recruitment | 4 | 0.901 | 0.923 | 0.714 |
| AI-Enabled Training | 4 | 0.912 | 0.931 | 0.728 |
| AI-Driven Performance Management | 4 | 0.889 | 0.916 | 0.698 |
| AI-Supported Engagement | 4 | 0.876 | 0.908 | 0.671 |
| Work Engagement | 9 | 0.951 | 0.958 | 0.697 |
| Digital Literacy | 10 | 0.912 | 0.926 | 0.641 |

*Note.* CR = composite reliability; AVE = average variance extracted.

Discriminant validity was assessed using the Fornell-Larcker criterion and HTMT ratio. As shown in Table 3, the square root of AVE for each construct exceeded its correlations with other constructs, satisfying the Fornell-Larcker criterion. HTMT values ranged from 0.312 to 0.724, all below the 0.85 threshold, providing further evidence of discriminant validity.

**Table 3**

*Discriminant Validity (Fornell-Larcker Criterion)*

| Construct | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1. AI-Assisted Recruitment | **0.845** | | | | | |
| 2. AI-Enabled Training | 0.612 | **0.853** | | | | |
| 3. AI-Driven Performance Management | 0.534 | 0.598 | **0.835** | | | |
| 4. AI-Supported Engagement | 0.487 | 0.523 | 0.612 | **0.819** | | |
| 5. Work Engagement | 0.412 | 0.478 | 0.521 | 0.489 | **0.835** | |
| 6. Digital Literacy | 0.321 | 0.387 | 0.412 | 0.398 | 0.445 | **0.801** |

*Note.* Diagonal values (bold) represent the square root of AVE.

### *4.2 Descriptive Statistics and Correlations*

Table 4 presents the descriptive statistics and zero-order correlations among the study variables. AI-enabled HRM practices were positively and significantly correlated with work engagement ($r = 0.521$, $p < 0.001$) and digital literacy ($r = 0.412$, $p < 0.001$). Digital literacy was also positively correlated with work engagement ($r = 0.445$, $p < 0.001$). These correlations provide preliminary support for the hypothesized relationships.

**Table 4**

*Descriptive Statistics and Correlations*

| Variable | Mean | SD | 1 | 2 | 3 |
|---|---|---|---|---|---|
| 1. AI-Enabled HRM Practices | 3.72 | 0.78 | 1 | | |
| 2. Digital Literacy | 3.85 | 0.71 | 0.412** | 1 | |
| 3. Work Engagement | 4.62 | 1.12 | 0.521** | 0.445** | 1 |

*Note.* **p < 0.01.

### *4.3 Structural Model Assessment (PLS-SEM)*

The structural model was assessed using PLS-SEM with bootstrapping (5,000 resamples). Table 5 presents the results of hypothesis testing. H1 proposed that AI-enabled HRM practices have a positive effect on employee work engagement. The results support this hypothesis ($\beta = 0.412$, $t = 7.234$, $p < 0.001$), indicating that for everyone standard deviation increase in AI-enabled HRM practices, work engagement increases by 0.412 standard deviations.

H2 proposed that employee digital literacy moderates the relationship between AI-enabled HRM practices and work engagement. The interaction term (AI-Enabled HRM × Digital Literacy) was significant ($\beta = 0.156$, $t = 3.421$, $p < 0.01$), supporting H2. The positive interaction coefficient indicates that the positive effect of AI-enabled HRM practices on work engagement is stronger for employees with higher digital literacy. Figure 1 presents the interaction plot, which shows that the slope of the relationship between AI-enabled HRM practices and work engagement is steeper for high digital literacy employees compared to low digital literacy employees.

**Table 5**

*Structural Model Results (PLS-SEM)*

| Hypotheses | Path | β | SE | t-value | p-value | Result |
|---|---|---|---|---|---|---|
| H1 | AI-HRM → Work Engagement | 0.412 | 0.057 | 7.234 | <0.001 | Supported |
| H2 | AI-HRM × Digital Literacy → Work Engagement | 0.156 | 0.046 | 3.421 | 0.001 | Supported |

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### *4.4 Hierarchical Regression Analysis*

**Table 6**

*Hierarchical Regression Analysis*

| Predictor | β | t | $R^2$ | $\Delta R^2$ | F |
|---|---|---|---|---|---|
| Step 1: Control Variables | | 0.08 | 2.134 | | |
| Step 2: AI-Enabled HRM | 0.398** | 6.89 | 0.41 | 0.336** | 48.72 |
| Digital Literacy | 0.312** | 5.42 | | | |
| Step 3: AI-HRM × Digital Literacy | 0.148** | 3.41 | 0.43 | 0.021** | 11.68 |

*Note.* **$p < 0.001$, **$p < 0.01$; Dependent Variable = Work Engagement.

### *4.5 Simple Slope Analysis*

To further interpret the moderating effect, simple slope analysis was conducted at three levels of digital literacy: low (mean - 1 SD), medium (mean), and high (mean + 1 SD). As shown in Table 7, the effect of AI-enabled HRM practices on work engagement was significant at all three levels of digital literacy but was strongest at high levels. Specifically, the effect was $\beta = 0.276$ ($p < 0.001$) at low digital literacy, $\beta = 0.412$ ($p < 0.001$) at medium digital literacy, and $\beta = 0.548$ ($p < 0.001$) at high digital literacy. This pattern confirms that digital literacy enhances the positive effect of AI-enabled HRM practices on work engagement.

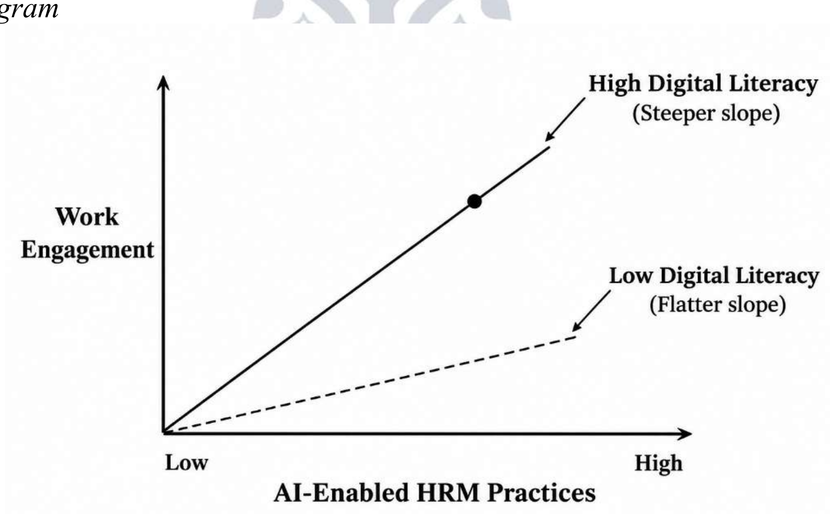
**Table 7**

*Simple Slope Analysis*

| Digital Literacy Level | Effect (β) | SE | t-value | p-value |
|---|---|---|---|---|
| Low (-1 SD) | 0.276 | 0.068 | 4.059 | <0.001 |
| Medium (Mean) | 0.412 | 0.057 | 7.234 | <0.001 |
| High (+1 SD) | 0.548 | 0.071 | 7.718 | <0.001 |

**Figure 2**

*Moderating Effect Diagram*




### *4.6 Post Hoc Analysis: Relative Importance of AI-HRM Dimensions*

A post hoc analysis was conducted to examine the relative importance of the four dimensions of AI-enabled HRM practices in predicting work engagement. Table 8 presents the results. AI-driven performance management emerged as the strongest predictor ($\beta = 0.198$, $p < 0.001$), followed by AI-enabled training and development ($\beta = 0.167$, $p < 0.001$), AI-assisted recruitment ($\beta = 0.112$, $p < 0.01$), and AI-supported employee engagement ($\beta = 0.089$, $p < 0.05$). These findings suggest that performance management and training are the most impactful applications of AI for enhancing work engagement.

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**Table 8**
*Relative Importance of AI-HRM Dimensions*

| Dimension | β | t-value | p-value |
|---|---|---|---|
| AI-Driven Performance Management | 0.198 | 4.672 | <0.001 |
| AI-Enabled Training and Development | 0.167 | 3.891 | <0.001 |
| AI-Assisted Recruitment | 0.112 | 2.734 | 0.006 |
| AI-Supported Employee Engagement | 0.089 | 2.128 | 0.034 |

## 5. Discussion

### *5.1 Theoretical Implications*

The study has a number of important theoretical contributions to the literature concerning AI-enabled HRM and employee work engagement. First, it builds on the Job Demands-Resources (JD-R) model by conceptualizing AI-based HRM practices as a multidimensional job resource that could motivate work engagement. The results show that HRM practices that utilize AI are job resources that meet employees' needs for competence, autonomy and relatedness, thus enhancing engagement, with AI-based performance management practices and AI-Enhanced Training and Development practices being particularly important. The discovery resonates with the JD-R model's suggestion that job resources can be motivating and applies it to the setting of AI-supported HR systems.

Second, this study tackles the findings that are inconsistent in the literature about the relationship between the adoption of AI and employee engagement. Some research has found a positive correlation while others have demonstrated the negative impacts such as technostress and loss of autonomy. This study's findings showed the impact of AI-enabled HRM on engagement depends on the employees' capability to effectively use AI resources and also revealed that employee digital literacy is a moderator. The results are consistent with the proposition of the JD-R model that personal resources moderate the relationship between job resources and engagement (Bakker & Demerouti, 2017). It further builds on the work of Zhan and Xie (2025) who concluded that digital literacy serves as a mediator between the workplace digitalization and work engagement.

Thirdly, the identification of AI-based performance management as the top predictor of work engagement has theoretical significance. The motivational potential of AI-powered HRM is highest when AI is applied in the context of feedback, reward, and facilitation of goal achievement. This fits with the job characteristics model (Hackman & Oldham 1976), which suggests feedback and task significance are significant contributors to internal work motivation. These job attributes may be further improved by AI-powered performance management systems, which offer real-time, customized feedback and make employees' contributions more transparent.

### *5.2 Practical Implications*

This study has a number of practical applications for human resource practitioners and organizational leaders. First, it is important to note that implementing HRM practices aided by AI can boost employee work engagement, and that this is not guaranteed. HR leaders need to create AI-powered HRM systems that are not burdensome but helpful by giving employees valuable feedback, development opportunities, and autonomy support. It takes system design, implementation, and change management to be carefully considered.

Second, the moderating influence of digital literacy implies that there is a need for the organisations to focus on digital literacy training and development. Those who have less digital literacy are less likely to gain from AI-driven HRM and could find that these are stressors. Targeted training initiatives should be implemented to improve the capacity of employees in using AI-driven HR solutions, understanding how algorithms operate, and utilizing algorithmic results to boost personal and professional development. Organizations should prioritize targeted training initiatives to ensure employees can navigate AI-driven HR systems, grasp how algorithms work, and use algorithmic insights to strengthen personal and professional growth. The term 'digital literacy' is important in the digital world as pointed out by Shatila et al. (2026). Digital transformation practices, as well as employee performance should also be supported by strengthening resource management practices in the organizations, especially SMEs (Aurangzeb et al., 2021). Implementing AI systems in the workplace should be done in a way that is ethical and respects the diversity of workplace norms (Usama et al., 2022).

Thirdly, these findings indicate that HR leaders should focus on AI applications in the area of performance management as it can be the best predictor of engagement. Technology solutions that incorporate AI can improve employee engagement by providing real-time feedback, recognizing accomplishments, and aiding in goal setting. Organizations need to make sure that these systems are seen as transparent, fair and conducive to employee development.

Fourth, organizations need to be aware of the possibility of unintended consequences arising from the use of AI in HRM, such as technostress, privacy issues, and the lack of human interaction. The International Labour Organization (2025) states that "If not designed appropriately, AI may lead to less fairness, transparency and trust in the workplace. To effectively implement AI in HR, it is crucial for leaders to do so with the employee in mind, focusing on employee well-being, transparency, and a strategy that involves listening to their voice.

### *5.3 Limitations and Directions for Future Research*

There are a number of limitations of this study that should be noted. First, the cross-sectional design precludes causal inferences. The theoretical framework indicates that there is a link between the use of AI-based HRM practices and work engagement, but it is equally possible that employees that are engaged are more likely to adopt AI practices for HRM. Longitudinal designs should be used in further studies to explore the direction of this relationship.

Secondly, common method bias could be introduced by the use of self-report measures. The first factor accounted for 34.2% of the variance, which was below the 50% cutoff point suggested by Harman, so common method bias was not considered to be a significant issue; future research could include multiple sources of data or objective measures to rule out the common method bias issue.

Third, the sample was taken from the three sectors (IT, banking and telecom) of Pakistan, which may restrict the generalizability of the findings. Further studies should be conducted in other cultural contexts and industries to validate the results of the current study and improve external validity. The results might be relevant to the emerging economies, where digital literacy is and isn't widespread.

Fourth, in this study, digital literacy was studied as a single moderator. Further studies are recommended to investigate other moderators and mediators that could affect the link between AI-based HRM and engagement. Factors that could act as moderators are AI trust, organizational culture, and leadership support. Between lessness, fairness and psychological safety are potential mediators. Other studies in the future can also explore the financial aspects of economic value-added and stock performance to measure the overall effect of AI-powered HRM on the organization (Pasha et al., 2019).

Lastly, the study did not provide a detailed analysis of the impact of AI-enabled HRM on specific outcomes, which is another limitation. Further studies examining the differential impacts of various forms of AI in HRM practices (such as predictive HRM, HRM chatbots, sentiment analysis) on employee engagement and the moderating effects of context are needed.

## 6. Conclusion

The research of the current study showed that the relationship between AI-assisted HRM practices and work engagement of employees act as moderating variable. Based on the theories of Job Demands-Resources and Social Exchange Theory, the study introduces and tests a moderated model using the data of 412 employees from Pakistan's IT, banking, and telecom industries. The results confirm the hypothesized relationships: AI-based HRM practices positively impact work engagement, with a stronger influence for those who have a high level of digital literacy.

The study is a significant contribution both theoretically and practically. On a theoretical level, it extends the JD-R model by showing how AI-powered HRM practices act as job resources that contributes to employee engagement, depending on their digital literacy. In practical terms, it offers guidance and insights based on solid evidence for HR professionals aiming to harness the benefits of AI investments and minimize potential risks.

AI's ongoing evolution in the HRM landscape underscores the need to understand its impact on employee engagement, which will continue to be a key area of focus. It is the first study to contribute a deeper understanding of how AI-facilitated HRM can positively influence employee work engagement (not negatively) under certain conditions. Further studies are needed to continue to investigate the multi-facet relationships between technology, individual differences, and organizational outcomes in the digital age.

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**Contribution of Authors**

All the authors participated in the ideation, development, and final approval of the manuscript, making significant contributions to the work reported.

**Conflict of Interest Statement**

The authors declare no conflicts of interest.

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**Informed Consent**

Informed consent was obtained from all individual participants included in the study.

**Ethical Approval**

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

**References**

Alizai, S. H., Asif, M., & Rind, Z. K. (2021). Relevance of motivational theories and firm health. *International Journal of Management, 12*(3), 1130–1137.

Asif, M. (2021). *Contingent effect of conflict management towards psychological capital and employees' engagement in financial sector of Islamabad* [Doctoral dissertation, Preston University]. https://doi.org/10.13140/RG.2.2.17616.79360

Asif, M. (2022). Integration of information technology in financial services and its adoption by the financial sector in Pakistan. *Inverge Journal of Social Sciences, 1*(2), 23–35. https://doi.org/10.63544/ijss.v1i2.31

Asif, M., Imran, A., Joseph, V., Haqdad, U., Samraameer, & Asif, M. (2022). Mediating role of trust between emotional intelligence and project team performance in telecommunication sector. *PalArch's Journal of Archaeology of Egypt/Egyptology, 19*(4), 988–1005.

Asif, M., Khan, A., & Pasha, M. A. (2019). Psychological capital of employees' engagement: Moderating impact of conflict management in the financial sector of Pakistan. *Global Social Sciences Review, 4*(3), 160–172. https://doi.org/10.31703/gssr.2019(IV-III).15

Asif, M., Pasha, M. A., Shafiq, S., & Craine, I. (2022). Economic impacts of post COVID-19. *Inverge Journal of Social Sciences, 1*(1), 56–65. https://doi.org/10.63544/ijss.v1i1.6

Asif, M., & Shaheen, A. (2022). Creating a high-performance workplace by the determination of importance of job satisfaction, employee engagement, and leadership. *Journal of Business Insight and Innovation, 1*(2), 9–15.

Aurangzeb, Asif, M., & Amin, M. K. (2021). Resources management and SME's performance. *Humanities & Social Sciences Reviews, 9*(3), 679–689. https://doi.org/10.18510/hssr.2021.9367

Aurangzeb, D., & Asif, M. (2021). Role of leadership in digital transformation: A case of Pakistani SMEs. In *Fourth International Conference on Emerging Trends in Engineering*.

Aurangzeb, Mushtaque, T., Tunio, M. N., Zia-ur-Rehman, & Asif, M. (2021). Influence of administrative expertise of human resource practitioners on the job performance: Mediating role of achievement motivation. *International Journal of Management, 12*(4), 408–421. https://doi.org/10.34218/IJM.12.4.2021.035

Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology, 22*(3), 273–285. https://doi.org/10.1037/ocp0000056

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–336). Lawrence Erlbaum.

Gallup. (2024). *State of the global workplace: 2024 report*. Gallup.

Grand View Research. (2025). *Artificial intelligence in HR market size report, 2025–2030*. Grand View Research.

Hackman, J. R., & Oldham, G. R. (1976). Motivation through the design of work: Test of a theory. *Organizational Behavior and Human Performance, 16*(2), 250–279. https://doi.org/10.1016/0030-5073(76)90016-7

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.

International Labour Organization. (2025). *AI and the future of work: Human-centred approaches*. ILO.

Kim, S., Lee, H., & Park, J. (2024). The development of a digital literacy instrument to measure the frequency of digital skills usage in the workplace. *Human Resource Development Quarterly, 35*(2), 189–210.

Pasha, M. A., Ramzan, M., & Asif, M. (2019). Impact of economic value-added dynamics on stock prices fact or fallacy: New evidence from nested panel analysis. *Global Social Sciences Review, 4*(3), 135–147. https://doi.org/10.31703/gssr.2019(IV-III).13

Prikshat, V., Malik, A., & Budhwar, P. (2023). AI-augmented HRM: Antecedents, assimilation and multilevel consequences. *Human Resource Management Review, 33*(1), Article 100860. https://doi.org/10.1016/j.hrmr.2021.100860

Schaufeli, W. B., Bakker, A. B., & Salanova, M. (2006). The measurement of work engagement with a short questionnaire: A cross-national study. *Educational and Psychological Measurement, 66*(4), 701–716. https://doi.org/10.1177/0013164405282471

Shahid, N., Asif, M., & Pasha, A. (2022). Effect of internet addiction on school going children. *Inverge Journal of Social Sciences, 1*(1), 12–47. https://doi.org/10.63544/ijss.v1i1.3

Shatila, K., Yela Aránega, A., & del Val Núñez, M. T. (2026). Leveraging AI for talent management: From talent acquisition to succession planning. In *Navigating AI in business* (pp. 151–175). Springer Nature.

Usama, H. A., Riaz, M., Khan, A., Begum, N., Asif, M., & Hamza, M. (2022). Prohibition of alcohol in Quran and Bible (A research and analytical review). *PalArch's Journal of Archaeology of Egypt/Egyptology, 19*(4), 1202–1211.

Zhan, X., & Xie, S. (2025). Linking workplace digitalization to work engagement: Evidence from China public sector organizations. *Frontiers in Psychology, 16*, Article 1455250. https://doi.org/10.3389/fpsyg.2025.1455250