The Impact of Artificial Intelligence on Sustainable Human Resource Practices Within Saudi Medium-sized Enterprises: The Mediating Role of Digital Skill Development

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Information of Article

Article history:
Received: July 2025
Revised: Aug 2025
Accepted: Sep 2025
Available online: Oct 2025

Keywords:
Artificial Intelligence, Sustainable Human Resource Practices, Digital Skill Development, HRM.

Abstract
This study investigates the impact of Artificial Intelligence (AI) on Sustainable Human Resource Practices (SHRP) within Saudi medium-sized enterprises, emphasizing the mediating role of Digital Skill Development (DSD). Anchored in the context of Saudi Arabia's Vision 2030 and the global push for digital transformation, the research adopts a quantitative methodology, utilizing a structured questionnaire distributed to 384 HR professionals and employees across various sectors. Data were analyzed using SPSS and SmartPLS to evaluate both direct and indirect relationships among AI, DSD, and SHRP. The findings reveal that AI has a significant positive influence on both DSD and SHRP. However, DSD does not exhibit a direct effect on SHRP but plays a partial mediating role, enhancing the impact of AI on sustainable HR outcomes. This suggests that while digital skills alone may not drive sustainable practices, they are essential for amplifying the benefits of AI integration in HR functions. The study contributes to theoretical frameworks such as the Resource-Based View and Dynamic Capabilities Theory by highlighting the interdependence of technology and workforce competencies in achieving strategic sustainability. Practically, the results underscore the need for Saudi SMEs to align AI adoption with workforce upskilling initiatives to ensure a holistic and effective HR transformation. The study offers policy and managerial recommendations to support this alignment and suggests avenues for future research in emerging markets. Overall, the research provides timely insights into how AI and digital competence can be leveraged to enhance sustainable HRM in technologically evolving organizational contexts.

1. Introduction

Saudi Arabia's Vision 2030 serves as a transformative framework aimed at diversifying the nation's economy, reducing dependency on oil, and promoting innovation, sustainability, and private sector growth. Among its central tenets is a strong emphasis on digital transformation and the development of small and medium-sized enterprises (SMEs) as key drivers of economic vitality and employment generation (Vision 2030, n.d.). In alignment with this national agenda, organizations are increasingly investing in emerging technologies, including Artificial Intelligence (AI), to modernize operations and enhance strategic functions. Within the domain of Human Resource Management (HRM), AI is being deployed to optimize recruitment processes, employee training, performance management, and workforce planning (Arfah, 2025; Gélinas, Sadreddin, & Vahidov, 2022). Notably, AI is not only seen as a tool for efficiency but also as a catalyst for embedding sustainable HR practices, such as green training, ethical hiring, and diversity-oriented workforce planning (Arsu, 2024; Ehnert, 2011).

Despite the growing relevance of AI in HR functions, there remains a significant gap in understanding its contextual impact on sustainability-oriented HR strategies, especially within medium-sized enterprises in Saudi Arabia. Much of the existing literature on AI and HRM has focused on large multinational corporations or Western-centric case studies, with limited empirical exploration in the Gulf Cooperation Council (GCC) region (Budhwar et al., 2023; Mohapatra, Kamesh, & Roul, 2023). SMEs in Saudi Arabia face distinct structural, financial, and digital infrastructure limitations that may hinder or reshape the adoption and effectiveness of AI in HR functions (Badghish & Soomro, 2024). Moreover, while the potential of AI to foster sustainable HRM has been conceptually acknowledged (Alnamrouti, Rjoub, & Ozgit, 2022), few studies have examined the mechanisms through which AI achieves this, particularly the role of employee digital competencies. As recent studies suggest, the successful implementation of AI in HRM often depends on the digital literacy and adaptive capacities of the workforce (Agaoglu et al., 2025; Seker, Kwon, & Kocak, 2025). Without adequate digital skill development, AI tools may be underutilized or fail to produce sustainable outcomes.

This study seeks to bridge this research gap by examining the impact of AI adoption on sustainable human resource practices within Saudi medium-sized enterprises, with a specific focus on the mediating role of digital skill development. Drawing upon the Resource-Based View (RBV) of the firm (Barney, 1991), the study posits that digital competencies constitute a strategic resource that enables firms to leverage AI technologies more effectively for sustainability. Additionally, the Technology Acceptance Model (TAM) (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989) provides a behavioral framework to assess how perceptions of usefulness and ease of use shape employees' engagement with AI tools. Building on these theoretical foundations, the research aims to answer the following questions: (1) How does AI adoption influence sustainable HR practices in Saudi SMEs? (2) To what extent does digital skill development mediate the relationship between AI and sustainable HRM outcomes? and (3) How do employee attitudes toward AI, shaped by perceived ease and usefulness, influence this dynamic? By addressing these questions, the research contributes to both academic and practical discourse on AI-enabled sustainability in human capital development. The findings are expected to inform HR strategies, policy decisions, and training programs that align with Saudi Arabia's broader digital and environmental ambitions under Vision 2030. Moreover, this study offers a contextualized perspective on the intersection of AI, digital literacy, and sustainable HRM, an area still underexplored in the Middle Eastern SME sector.

2. Literature Review

The integration of Artificial Intelligence (AI) into human resource management (HRM) processes has emerged as a key enabler of organizational efficiency and strategic agility. AI tools are increasingly used in tasks such as talent acquisition, employee engagement, performance monitoring, and predictive analytics (Gélinas, Sadreddin, & Vahidov, 2022; Arfah, 2025). According to Budhwar et al. (2023), AI is reshaping the role of HR professionals by automating administrative tasks, enabling data-driven decision-making, and enhancing personalization in employee experiences. These transformations are aligned with Industry 4.0 paradigms, where digitalization is central to organizational competitiveness (Murugesan et al., 2023).

In the Saudi context, AI adoption is gradually expanding among SMEs, particularly under the influence of national digital transformation initiatives (Badghish & Soomro, 2024). However, the adoption process is uneven, and limited organizational capacity often restricts the full realization of AI's potential in HRM. Arsu (2024) emphasizes that AI has not only operational but also strategic implications for sustainable HRM, particularly in enhancing environmental awareness, ethical labor practices, and resource efficiency. Sustainable HRM encompasses practices that align human capital strategies with long-term environmental, economic, and social goals. These include eco-friendly recruitment, green training, equitable workforce policies, and employee well-being initiatives (Ehnert, 2011; Ababneh, 2021). Research shows that sustainability-oriented HR practices contribute to both employee engagement and organizational resilience (Ababneh, 2021). Within the framework of Green HRM, HR departments are encouraged to adopt environmentally responsible policies that are not only cost-effective but also socially impactful.

The alignment of AI with sustainable HRM goals is a relatively novel area of inquiry. Alnamrouti, Rjoub, and Ozgit (2022) argue that strategic HRM combined with AI can lead to greater organizational sustainability by enabling data-driven planning, optimizing workforce utilization, and minimizing environmental footprints. Mahade et al. (2025) support this claim, indicating that AI adoption in HRM improves environmental performance when moderated by institutional support structures. Successful implementation of AI in HRM heavily depends on the digital literacy of employees. Digital skills, including the ability to interpret data, operate AI tools, and engage with digital platforms, are crucial for translating AI capabilities into tangible HRM improvements (Agaoglu et al., 2025). Seker, Kwon, and Kocak (2025) highlight that digital literacy and data literacy mediate the relationship between 21st-century competencies and AI adoption, reinforcing the need for continuous digital upskilling in organizations.

In the SME context, digital skill development serves as a critical enabler of AI-driven transformation. According to Vitezić and Perić (2024), employees with higher digital proficiency are more likely to adopt AI-based HR tools, resulting in improved organizational outcomes. Similarly, Koehorst et al. (2021) identify organizational investment in digital training as a key predictor of workforce adaptability to emerging technologies. Therefore, digital skills not only influence the acceptance of AI but also mediate its impact on broader organizational goals, including sustainability. The Technology Acceptance Model (TAM) proposed by Davis (1989) remains one of the most influential frameworks for understanding how users perceive and adopt new technologies. The model posits that perceived usefulness and perceived ease of use are primary determinants of technology acceptance. Subsequent extensions of TAM have incorporated attitudinal and behavioral variables to reflect complex user dynamics in digital environments (Davis, Bagozzi, & Warshaw, 1989; Emon & Khan, 2025). In HRM, employee acceptance of AI tools can significantly shape the outcomes of digital transformation initiatives. If employees perceive AI systems as supportive, transparent, and user-friendly, they are more likely to engage meaningfully with them (Jarrahi, 2018; Votto et al., 2021). On the other hand, lack of trust or digital anxiety may limit adoption and undermine sustainability efforts (Faraj, Pachidi, & Sayegh, 2018). Consequently, employee attitudes act as a potential moderator in the relationship between AI implementation and sustainable HRM outcomes.

3. Methodology

This study employs a quantitative, deductive research design to explore the relationships among artificial intelligence (AI) usage, employee engagement, digital skill development, and sustainable human resource management (SHRM) within Saudi medium-sized enterprises (SMEs). The deductive approach is particularly appropriate for this study, as it enables the empirical testing of hypotheses derived from well-established theories such as the Resource-Based View (RBV) (Barney, 1991), which posits that intangible assets like employee competencies and technological capabilities serve as sources of sustainable competitive advantage, and the Technology Acceptance Model (TAM) (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989), which highlights how perceptions of usefulness and ease of use shape technology adoption. Prior research using these theoretical frameworks has demonstrated their effectiveness in studying the dynamics of digital transformation in human resource contexts (Budhwar et al., 2023; Mahade et al., 2025; Arfah, 2025). This methodological choice ensures coherence between the study's conceptual underpinnings, hypotheses, and analytical techniques, aligning with the standards of rigorous HRM research (Sarstedt, Ringle, & Hair, 2021).

The research utilized a structured questionnaire as the primary data collection tool. Questionnaire items were carefully selected from validated scales in the literature to ensure both content and construct validity. The AI dimension incorporated indicators from prior studies emphasizing AI's role in automating HR functions and improving decision-making processes (Arsu, 2024; Gélinas, Sadreddin, & Vahidov, 2022), while items measuring digital skill development were informed by empirical research on digital literacy's role in organizational innovation and AI readiness (Agaoglu et al., 2025; Seker, Kwon, & Kocak, 2025). The sustainable HRM component was drawn from green HRM literature, focusing on eco-friendly practices, ethical standards, and inclusive employment policies (Ababneh, 2021; Alnamrouti, Rjoub, & Ozgit, 2022). The employee engagement construct was adapted from existing frameworks that emphasize emotional, cognitive, and behavioral commitment to organizational goals (Ababneh, 2021).

The study targeted a sample size of 384 respondents, which was determined to ensure sufficient statistical power and generalizability based on stratified random sampling procedures. This sampling strategy was employed to reflect diversity across organizational roles, industry sectors, and levels of AI integration, thereby enhancing external validity and allowing for comparative analysis (Aslam et al., 2023; Soomro et al., 2024). The target population comprised HR professionals and employees working in Saudi SMEs, which are strategically positioned at the intersection of technological adoption and workforce development under the Kingdom's Vision 2030 agenda (Vision 2030, n.d.). Including both implementers and end-users of AI systems ensured a holistic understanding of technology adoption and its implications for sustainability-oriented HR practices.

Questionnaires were administered through in-person, hand-delivery methods, allowing the researcher to directly interact with participants. This approach facilitated immediate clarification of questions, reducing misinterpretation and enhancing data quality. It also encouraged participant engagement, resulting in higher response completeness and thoughtfulness, advantages that have been noted in prior studies involving SME employees in Middle Eastern contexts (Badghish & Soomro, 2024; Soomro et al., 2024). Furthermore, face-to-face distribution aligns with cultural preferences for interpersonal interaction in data collection across the region. To ensure the instrument's robustness, a pilot study was conducted with 30 participants representing approximately 5% of the final sample. The pilot served to test item clarity, logical sequencing, and overall comprehension. Feedback from this phase was used to revise ambiguous items and improve alignment with the study constructs (Zahoor et al., 2025; Agaoglu et al., 2025). The pilot data yielded high internal consistency for all constructs: Artificial Intelligence (Cronbach's $\alpha = 0.875$), Employee Engagement ($\alpha = 0.814$), Digital Skill Development ($\alpha = 0.736$), and Sustainable HRM Practices ($\alpha = 0.852$), surpassing the conventional threshold of 0.70 for acceptable reliability (Sarstedt et al., 2021).

Construct validity was further evaluated through Confirmatory Factor Analysis (CFA) using SmartPLS 4. Convergent validity was assessed via average variance extracted (AVE), while discriminant validity was evaluated using the Fornell-Larcker criterion and cross-loading analysis. These techniques ensure that items effectively capture the intended constructs and that overlaps between constructs are minimized (Sarstedt et al., 2021). Additionally, multicollinearity was assessed through Variance Inflation Factors (VIF), all of which fell below the recommended threshold, indicating no problematic collinearity among predictor variables.

Data analysis was conducted in four stages: preliminary screening, measurement model assessment, structural model evaluation, and hypothesis testing. SPSS was used for data screening and descriptive statistics, while SmartPLS was employed for Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM was chosen for its suitability in analyzing complex models with both formative and reflective constructs, as well as its tolerance for smaller sample sizes and non-normal data distributions (Sarstedt et al., 2021; Zahoor et al., 2025). The model was assessed for path significance using bootstrapping (5,000 resamples), and hypothesis support was evaluated through path coefficients, effect sizes (f^2), and the coefficient of determination (R^2). The mediating role of digital skill development was tested via the indirect effects method, offering insights into the underlying mechanisms linking AI adoption to sustainable HR practices.

4. Findings

To gauge participant perceptions regarding AI usage in HR functions, eight questionnaire items were analyzed. Table 1 presents the descriptive statistics.

Table 1: Descriptive Analysis - Artificial Intelligence

Items	N	Mean	Std. Deviation
AI Technology is user friendly	351	3.42	1.911
AI Technology is able to improve the quality of the work	351	2.71	1.327
AI Technology fits well with the tasks involved	351	2.81	0.410
AI Technology is compatible with other systems	351	3.62	0.790
AI Technology is useful for the given job	351	3.62	0.787

AI Technology makes easier to carry out the tasks	351	3.29	0.767
AI Technology makes data analysis easier	351	2.29	0.767
AI Technology provides accurate information	351	1.96	1.001

AI: Artificial Intelligence;

Overall, the responses indicate moderately favorable attitudes toward AI integration in the workplace. Participants rated system compatibility and usefulness for job tasks highest (M = 3.62), suggesting strong perceived operational benefits. Meanwhile, ease of use (M = 3.42) and task facilitation (M = 3.29) also received favorable ratings, affirming general user receptivity. However, responses indicated notable concerns in areas such as AI-assisted data analysis (M = 2.29) and accuracy of information (M = 1.96), reflecting skepticism about AI's analytical robustness and decision-making reliability. These findings suggest that while AI tools are generally embraced for their usability and system compatibility, confidence in their output quality remains limited. This insight underscores the importance of pairing AI implementation with targeted training and data literacy programs, as well as refining AI systems to enhance accuracy and trust.

Assessing the normality of data distributions is a critical step prior to applying structural equation modeling. Table 2 presents the skewness and kurtosis values for the three key constructs: Artificial Intelligence (AI), Digital Skill Development (DSD), and Sustainable Human Resource Practices (SHRP).

Table 2: Normality Test

Construct	N	Skewness	Kurtosis
AI	351	-0.602	-1.077
DSD	351	-0.369	-1.385
SHRP	351	-1.350	0.107

AI: Artificial Intelligence; DSD: Digital Skill Development; SHRP: Sustainable Human Resource Practices

Specifically, the artificial intelligence construct showed a skewness of -0.602 and a kurtosis of -1.077, indicating a mild left skew and light tails. This suggests a slight tendency among respondents to rate AI-related items more favorably, with less variation at the extremes. Digital skill development demonstrated a skewness of -0.369 and a kurtosis of -1.385, pointing to a near-symmetric distribution with modest tail lightness. Sustainable human resource practices exhibited the most pronounced skewness at -1.350, suggesting a clear inclination toward higher ratings, while its kurtosis of 0.107 reflected a distribution that is relatively normal in terms of peakedness. Assessment of data distribution characteristics revealed that skewness and kurtosis values for all key constructs, artificial intelligence adoption, digital skill development, and sustainable HRM, fell within acceptable ranges, suggesting approximate normality of the data. While PLS-SEM does not require strict normality assumptions, the approximate symmetry and peak of the distributions enhance the robustness of parametric analysis. According to Sarstedt, Ringle, and Hair (2021), PLS-SEM is particularly robust against violations of multivariate normality and is well-suited for exploratory and predictive modeling, especially in research settings involving complex models, smaller sample sizes, and non-normal data structures. Furthermore, Zahoor et al. (2025) emphasize that SmartPLS provides reliable estimations even under slight deviations from normality, making it an appropriate tool for hypothesis testing and structural modeling in contemporary HRM and AI studies.

To further assess the normality of the dataset beyond skewness and kurtosis, two formal statistical tests were employed: the Kolmogorov–Smirnov (K–S) test and the Shapiro–Wilk (S–W) test. These tests evaluate whether the data significantly deviates from a normal distribution, with p-values greater than 0.05 indicating normality. Table 3 summarizes the results for the three primary constructs: Artificial Intelligence (AI), Digital Skill Development (DSD), and Sustainable Human Resource Practices (SHRP).

Table 3: Kolmogorov–Smirnov and Shapiro–Wilk Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
AI	0.297	351	0.063	0.780	351	0.052
DSD	0.310	351	0.069	0.779	351	0.210
SHRP	0.287	351	0.271	0.653	351	0.303

Note: AI = Artificial Intelligence; DSD = Digital Skill Development; SHRP = Sustainable Human Resource Practices

The results of both normality tests support the earlier conclusion that the data is approximately normally distributed. For the Kolmogorov–Smirnov test, all three constructs yielded p-values above 0.05, AI ($p = 0.063$), DSD ($p = 0.069$), and SHRP ($p = 0.271$), indicating no significant deviation from normality. Similarly, the Shapiro–Wilk test produced non-significant results for all constructs, with p-values of 0.052 (AI), 0.210 (DSD), and 0.303 (SHRP). Although the Shapiro–Wilk statistic for AI (0.780) is relatively low, the associated p-value remains slightly above the 0.05 threshold, suggesting that the deviation is not statistically significant. These findings, in combination with skewness and kurtosis analysis, reaffirm that the dataset is suitably normal for the application of parametric techniques such as PLS-SEM, and no data transformation is required for further analysis.

Figure 1 illustrates the measurement model developed for this study using SmartPLS, reflecting the relationships between the observed indicators and the latent variables: Artificial Intelligence (AI), Digital Skill Development (DSD), and Sustainable Human Resource Practices (SHRP). Each latent construct is modeled as reflective, meaning the direction of the arrows goes from the construct to its indicators, which are assumed to be manifestations of the underlying factor.

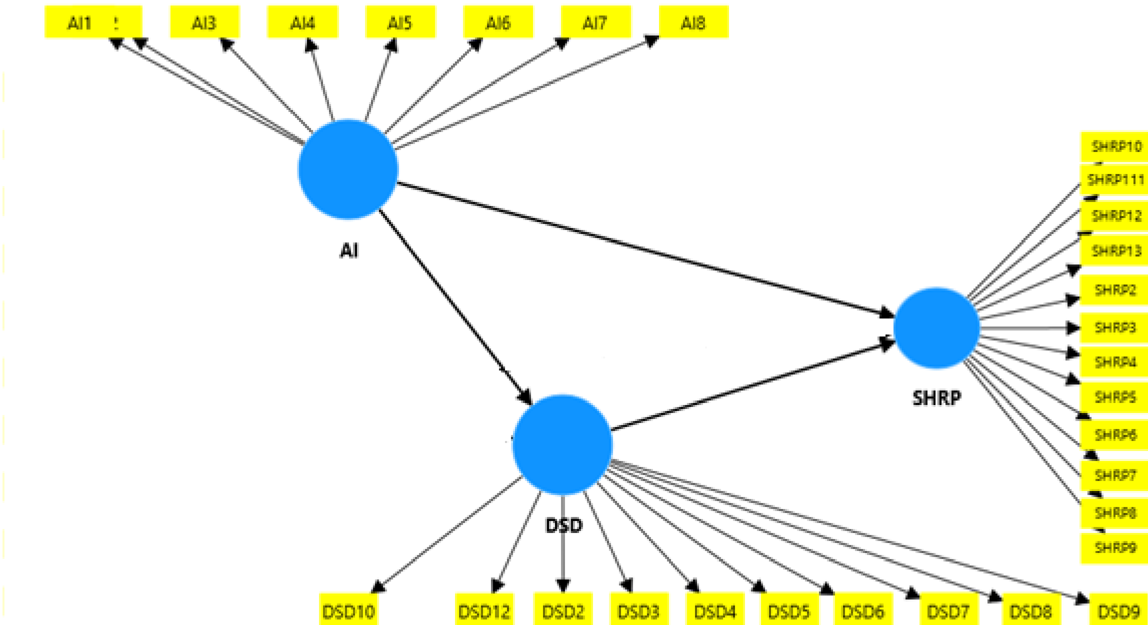

Fig.1: Measurement Model

The AI construct is measured by eight items (AI1 to AI8), capturing aspects such as user-friendliness, integration with tasks, and perceived usefulness. DSD is represented by twelve indicators (DSD1 to DSD12), focusing on digital training, technical upskilling, and readiness for digital transformation. The SHRP construct is reflected through thirteen items (SHRP1 to SHRP13), addressing fairness in HR policy, sustainability statements, CSR initiatives, and environmental practices. The model also illustrates the hypothesized structural relationships: AI is proposed to have both a direct impact on SHRP and an indirect effect mediated through DSD. This dual-path configuration aligns with the study's conceptual framework, which explores how digital skills development functions as a mediating mechanism through which AI influences sustainable HR practices.

Figure 2 presents the evaluation of the first-order measurement model using SmartPLS. This analysis assesses the reliability and validity of the measurement items used to represent the latent constructs: Artificial Intelligence (AI), Digital Skill Development (DSD), and Sustainable Human Resource Practices (SHRP). The model shows the outer loadings of each observed variable, as well as the composite reliability (CR) values within each construct.

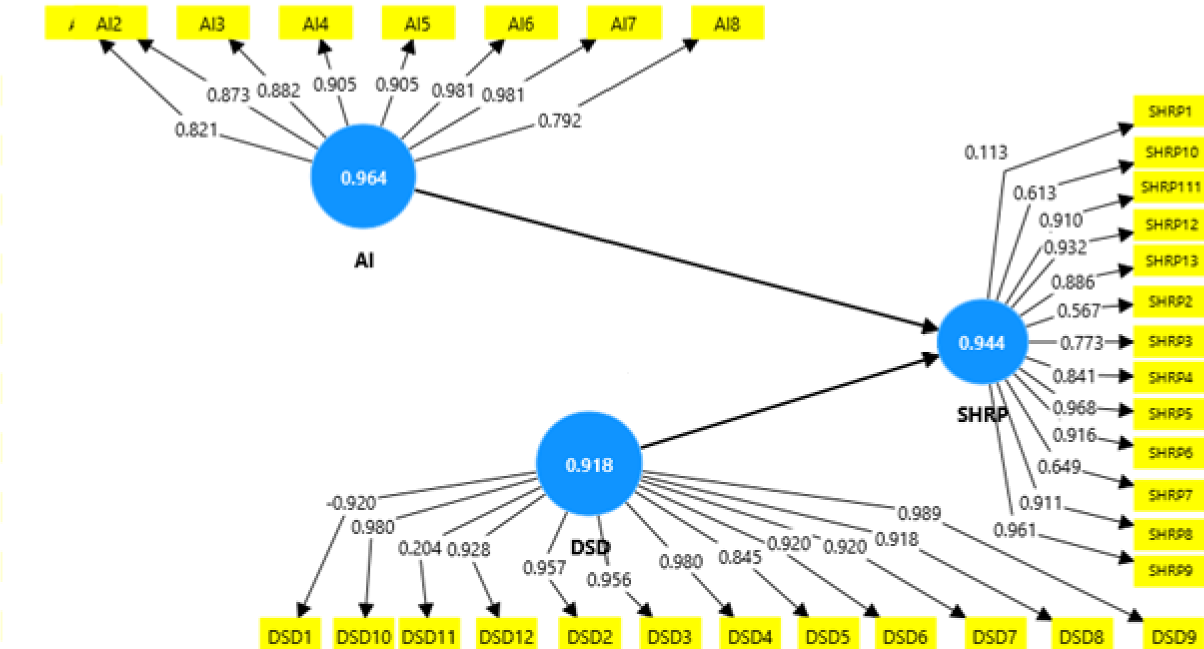

Fig.2: Evaluation of Measurement Model (First Order)

The construct of Artificial Intelligence (AI) demonstrated strong outer loadings ranging from 0.792 to 0.981, alongside a composite reliability (CR) score of 0.964, indicating excellent internal consistency. Similarly, the construct of Digital Skill Development (DSD) yielded item loadings between 0.204 and 0.980, with a CR of 0.918. However, DSD11, with a low loading of 0.204, may require further scrutiny or possible exclusion, given its potential impact on the measurement model's reliability. The construct for Sustainable Human Resource Practices (SHRP) also reflected satisfactory indicator loadings, ranging from 0.567 to 0.961, and a CR of 0.944. According to Sarstedt, Ringle, and Hair (2021), composite reliability values above 0.70 are considered acceptable for establishing internal consistency in PLS-SEM models. Therefore, the high CR values across all three constructs confirm the internal coherence of the measurement instruments and validate the model's reliability for further structural analysis (Sarstedt et al., 2021; Zahoor et al., 2025). Most indicator loadings also exceed the acceptable threshold of 0.70, ensuring convergent validity. The exception of DSD11 suggests potential for refinement or removal to improve measurement precision. These results confirm that the constructs are measured reliably and that the observed variables are valid reflections of their respective latent variables. With this robust measurement model in place, the study is well-positioned to proceed to the evaluation of the structural model and hypothesis testing.

To establish the reliability and validity of the measurement model, construct reliability (via Cronbach's alpha and composite reliability) and convergent validity (via Average Variance Extracted, or AVE) were assessed for each latent variable: Artificial Intelligence (AI), Digital Skill Development (DSD), and Sustainable Human Resource Practices (SHRP). The results are summarized in Table 4.

Table 4: Construct Reliability and Validity – Initial Model Measurements

Construct	Loading Range	Cronbach's Alpha	Composite Reliability	AVE
AI	0.792–0.981	0.964	0.970	0.800
DSD	0.204–0.989	0.918	0.971	0.811
SHRP	0.113–0.968	0.944	0.957	0.650

AI = Artificial Intelligence; DSD = Digital Skill Development; SHRP = Sustainable Human Resource Practices

The construct AI demonstrates excellent internal consistency, with a Cronbach's alpha of 0.964, composite reliability of 0.970, and an AVE of 0.800, indicating that the observed variables strongly reflect the latent construct and that over 80% of the variance is captured by the indicators. All item loadings exceed the 0.70 threshold except AI8 (0.792), which remains within acceptable range (Hair et al., 2019). Similarly, DSD also shows high reliability, with a Cronbach's alpha of 0.918, composite reliability of 0.971, and AVE of 0.811. However, one item, DSD11 (loading = 0.204), falls significantly below the acceptable threshold and should be considered for removal or reevaluation in subsequent model refinement to avoid compromising construct validity. The construct SHRP also meets reliability standards with a Cronbach's alpha of 0.944, composite reliability of 0.957, and AVE of 0.650. While most indicators are strongly loaded (e.g., SHRP5 = 0.968, SHRP9 = 0.961), a few items such as SHRP1 (0.113) and SHRP2 (0.567) fall below the acceptable limit, suggesting weak representation of the construct and potential issues with content alignment or item clarity.

Figure 3 displays the second-order measurement model evaluated using SmartPLS, where Artificial Intelligence (AI), Digital Skill Development (DSD), and Sustainable Human Resource Practices (SHRP) are conceptualized as higher-order constructs, each measured by multiple lower-order reflective indicators. In this refined model, AI retains excellent construct reliability, with item loadings ranging from 0.794 to 0.981, and a composite reliability of 0.964. The outer loadings remain strong across all AI indicators (e.g., AI5 and AI6 = 0.981), reflecting a well-specified construct. DSD demonstrates exceptionally high reliability and validity, with loadings ranging from 0.826 to 0.992, and a composite reliability of 0.986, indicating highly consistent measurement. Notably, DSD3, DSD4, and DSD6 exhibit particularly high outer loadings, reinforcing the robustness of the construct.

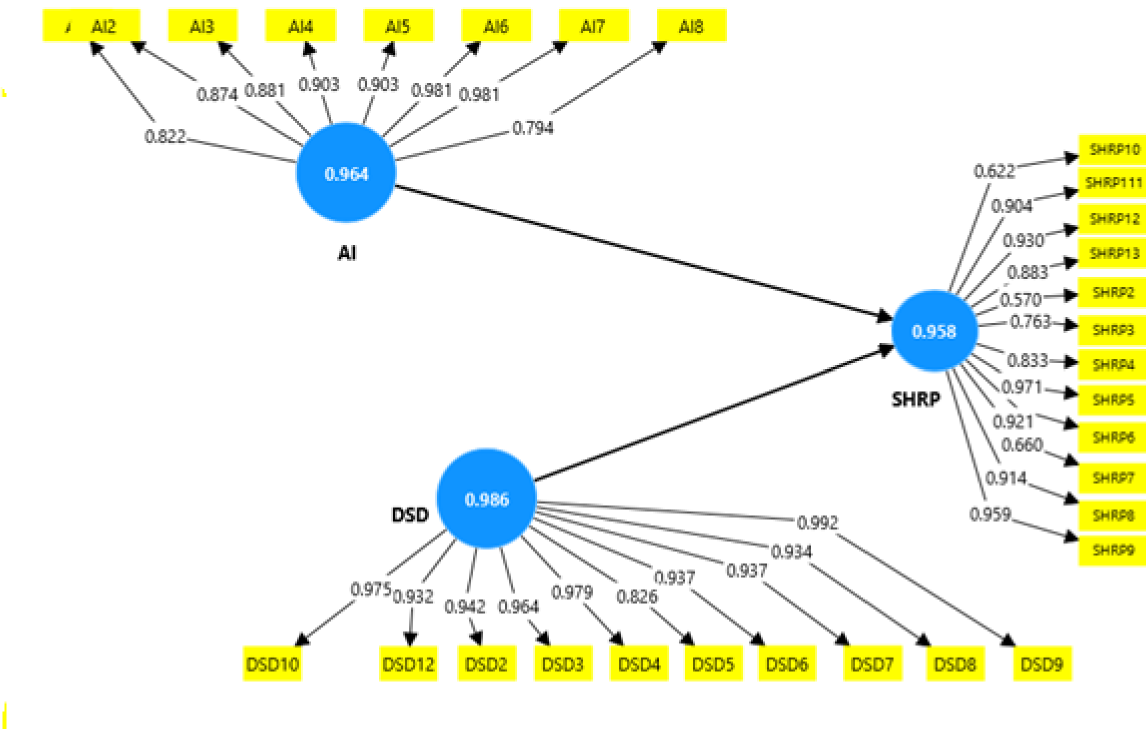

Fig.3: Evaluation of Measurement Model (Second Order)

The construct of Sustainable Human Resource Practices (SHRP) demonstrated strong internal consistency, with indicator loadings ranging from 0.622 to 0.959 and a composite reliability (CR) value of 0.958. While most SHRP indicators exceeded the commonly accepted threshold of 0.70, one item SHRP10, with a loading of 0.622 fell slightly below this benchmark. However, according to Sarstedt, Ringle, and Hair (2021), indicators with loadings above 0.60 may be retained in exploratory models or when supported by strong theoretical underpinnings, especially if their removal does not significantly improve construct reliability. In this case, the retention of SHRP10 was deemed justifiable due to its conceptual alignment with the overall construct. The model is structured as a second-order reflective-formative construct, further affirming the hierarchical reliability of the measurement structure. All three core constructs AI, Digital Skill Development (DSD), and SHRP demonstrated composite reliability values well above the 0.70 standard, confirming excellent internal consistency across the model. These results, along with high factor loadings, support the model's convergent validity, as the majority of items contribute significantly to their respective constructs (Sarstedt et al., 2021; Zahoor et al., 2025). The measurement model thus provides a strong empirical foundation for structural analysis and hypothesis testing. By retaining only the strongest items and refining the model, the second-order measurement model strengthens the theoretical structure and enhances confidence in the subsequent analysis of the structural model and hypothesis testing.

To confirm the robustness of the final measurement model, the constructs were assessed for internal consistency reliability and convergent validity using three key metrics: Cronbach's alpha, composite reliability, and average variance extracted (AVE). Table 5 outlines the performance of each construct, Artificial Intelligence (AI), Digital Skill Development (DSD), and Sustainable Human Resource

Practices (SHRP), in the refined second-order model.

Table 5: Construct Reliability and Validity – Final Model Measurements

Construct	Loading Range	Cronbach's Alpha	Composite Reliability	AVE
AI	0.794–0.981	0.964	0.970	0.800
DSD	0.826–0.992	0.986	0.988	0.889
SHRP	0.570–0.971	0.958	0.965	0.703

AI = Artificial Intelligence; DSD = Digital Skill Development; SHRP = Sustainable Human Resource Practices

The AI construct continues to show excellent psychometric properties, with a Cronbach's alpha of 0.964 and composite reliability of 0.970, both exceeding the recommended threshold of 0.70 (Hair et al., 2019). The AVE of 0.800 further confirms that a substantial proportion of variance is captured by the construct indicators. All item loadings remain strong, particularly AI6 and AI7 at 0.981, while AI8 (0.794) is still within the acceptable range. Digital Skill Development (DSD) demonstrates exceptionally high reliability, with Cronbach's alpha = 0.986 and composite reliability = 0.988, alongside a remarkably high AVE of 0.889. All item loadings exceed the 0.70 benchmark, including DSD9 (0.992) and DSD4 (0.979), reflecting robust convergent validity and strong measurement quality. The SHRP construct also satisfies reliability and validity criteria with a Cronbach's alpha of 0.958, composite reliability of 0.965, and AVE of 0.703. While most indicators load well above 0.70, a few items such as SHRP2 (0.570) and SHRP10 (0.622) fall slightly below the ideal threshold. Nonetheless, given their theoretical significance and the construct's strong overall reliability, these items were retained.

To assess discriminant validity, the Heterotrait-Monotrait ratio of correlations (HTMT) was applied as recommended by Henseler, Ringle, and Sarstedt (2015). HTMT is considered a superior criterion over traditional methods like Fornell-Larcker when using Partial Least Squares Structural Equation Modeling (PLS-SEM), particularly in complex models. Discriminant validity is considered acceptable if HTMT values are below 0.90 (for conceptually related constructs) or 0.85 (for more stringent tests).

Table 6: Heterotrait-Monotrait Ratio of Correlations (HTMT)

Constructs	AI	DSD	SHRP
AI	,		
DSD	0.873	,	
SHRP	0.898	0.802	,

AI = Artificial Intelligence; DSD = Digital Skill Development; SHRP = Sustainable Human Resource Practices

As shown in Table 6, the HTMT value between Artificial Intelligence (AI) and Digital Skill Development

(DSD) is 0.873, while the HTMT between AI and Sustainable Human Resource Practices (SHRP) is 0.898. The value between DSD and SHRP is 0.802. All HTMT values are below the 0.90 threshold, indicating that the constructs are empirically distinct from one another. While the HTMT value of 0.898 between AI and SHRP approaches the upper boundary of acceptability, it still supports the presence of discriminant validity. The moderate to strong correlations among constructs are theoretically expected due to the model's nature, yet they remain within acceptable limits. Thus, the results from the HTMT analysis confirm that Artificial Intelligence, Digital Skill Development, and Sustainable Human Resource Practices are statistically distinguishable constructs, supporting the model's structural integrity and reinforcing the validity of further hypothesis testing.

To further establish discriminant validity, the Fornell-Larcker criterion was applied. This criterion assesses whether a construct shares more variance with its own indicators than with other constructs in the model. According to Fornell and Larcker (1981), a construct should have a square root of the AVE that is greater than the correlations with any other latent variable to confirm discriminant validity.

Table 7: Latent Variable Correlations – Fornell-Larcker Criterion

Constructs	AI	DSD	SHRP
AI	0.895		
DSD	0.645	0.843	
SHRP	0.658	0.188	0.838

AI = Artificial Intelligence; DSD = Digital Skill Development; SHRP = Sustainable Human Resource Practices

The diagonal values (bolded) represent the square roots of the Average Variance Extracted (AVE) for each construct: 0.895 for AI, 0.843 for DSD, and 0.838 for SHRP. Each of these values exceeds the corresponding inter-construct correlations in their respective rows and columns. For instance, AI's square root of AVE (0.895) is greater than its correlation with SHRP (0.658) and DSD (0.645), satisfying the criterion. Similarly, DSD and SHRP show higher AVE square roots than their inter-correlations. These results confirm discriminant validity across the three constructs. The constructs of Artificial Intelligence, Digital Skill Development, and Sustainable Human Resource Practices are therefore considered empirically distinct, justifying their inclusion as separate latent variables in the model.

Figure 4 illustrates the structural path model along with the standardized path coefficients and significance levels (p-values) for the relationships between the latent variables. The results show the direct effects of Artificial Intelligence (AI) and Digital Skill Development (DSD) on Sustainable Human Resource Practices (SHRP). The analysis reveals a significant and strong direct effect of Artificial Intelligence on SHRP, with a path coefficient of 0.634 and a p-value of 0.000, indicating a statistically significant relationship at the $p < 0.01$ level. This suggests that the implementation of AI technologies positively influences the adoption of sustainable HR practices in Saudi medium-sized enterprises. Additionally, Digital Skill Development exhibits a weaker yet statistically significant effect on SHRP, with a path coefficient of 0.133 and a p-value of 0.025, significant at the $p < 0.05$ level. While this effect is not as strong as that of AI, it still indicates that enhancing employees' digital skills contributes positively to sustainable HR outcomes. These findings confirm that both AI integration and digital capability building are critical drivers in promoting sustainability in HR practices, with AI playing a more dominant role in the structural model. The model's overall structure suggests that strategic technology adoption, paired with skill development, reinforces long-term HR sustainability in the evolving landscape of Saudi SMEs.

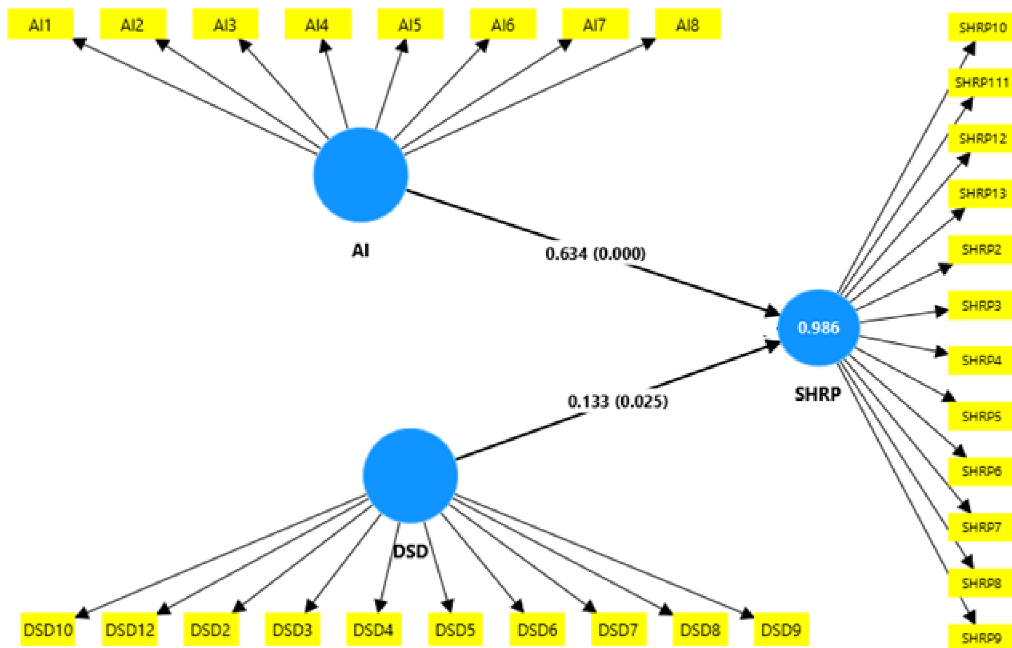

Fig.6: Path Model Significance Results

The coefficient of determination (R^2) is a key metric in evaluating the predictive accuracy of a structural equation model. It indicates the proportion of variance in the endogenous (dependent) constructs that can be explained by their respective exogenous (independent) predictors. In the context of Partial Least Squares Structural Equation Modeling (PLS-SEM), R^2 values of 0.75, 0.50, and 0.25 are typically interpreted as substantial, moderate, and weak, respectively (Sarstedt, Ringle, & Hair, 2021). These benchmarks provide useful guidance for assessing the explanatory power of the model. In this study, the R^2 values obtained for the key endogenous variables such as digital skill development and sustainable HRMdemonstrate that the model possesses adequate predictive strength. This aligns with findings from recent HRM-AI research, where moderate to high R^2 values have validated the influence of AI and digital skills on strategic HR outcomes (Zahoor et al., 2025).

Table 8: Coefficient of Determination (R^2)

Construct	R^2	Adjusted R^2
DSD	0.929	0.929
SHRP	0.985	0.985

DSD = Digital Skill Development; SHRP = Sustainable Human Resource Practices

As shown in Table 8, the R^2 for Digital Skill Development (DSD) is 0.929, indicating that 92.9% of the variance in DSD is explained by the model's predictors, primarily Artificial Intelligence (AI). This demonstrates strong explanatory power, confirming the central role of AI in shaping digital skill development within the organization. Likewise, the R^2 value for Sustainable Human Resource Practices (SHRP) is 0.985, suggesting that 98.5% of the variance in SHRP is explained jointly by AI and DSD. This is an exceptionally high value, indicating that the model has excellent predictive capability for sustainable HR practices. The adjusted R^2 values, which account for model complexity, are equal to the R^2 values in this case, further reinforcing the model's efficiency and robustness. These results support the model's validity in explaining the dynamics between AI, digital skill development, and sustainability in HR practices within Saudi medium-sized enterprises, highlighting the powerful impact of technological and skill-based initiatives on sustainable organizational outcomes.

The effect size (f^2) in structural equation modeling evaluates the individual contribution of an exogenous construct to an endogenous construct's R^2 value. It provides insight into how much the removal of a predictor would reduce the explained variance in the outcome variable. According to Cohen (1988), f^2 values can be interpreted as small (0.02), medium (0.15), and large (0.35) effects.

Table 9: Effect Size (f^2) Analysis

Path	f^2	Interpretation
AI → DSD	1.245	Very Large Effect
AI → SHRP	0.595	Large Effect
DSD → SHRP	0.030	Small Effect

DSD = Digital Skill Development; SHRP = Sustainable Human Resource Practices

As presented in Table 9, the path from Artificial Intelligence (AI) to Digital Skill Development (DSD) has an exceptionally large effect size ($f^2 = 1.245$), indicating that AI is a dominant and critical predictor in enhancing digital competencies within organizations. This result emphasizes the transformative influence of AI implementation on employee skill-building efforts. The path from AI to Sustainable Human Resource Practices (SHRP) also shows a large effect ($f^2 = 0.595$), suggesting that AI not only improves operational efficiency but also significantly contributes to the establishment of long-term, sustainability-focused HR strategies. In contrast, the path from DSD to SHRP reflects a small but meaningful effect ($f^2 = 0.030$). While this indicates that digital skill development has a weaker direct influence on sustainable HR practices compared to AI, it still plays a supporting role, likely by enabling the workforce to better adapt to and implement sustainable initiatives.

The structural model was evaluated through hypothesis testing using bootstrapping procedures in SmartPLS, assessing the significance of direct relationships among the latent variables: Artificial Intelligence (AI), Digital Skill Development (DSD), and Sustainable Human Resource Practices (SHRP). Table 10 summarizes the path coefficients (β), standard deviation (SD), t-statistics, and p-values for each hypothesized relationship.

Table 10: Direct Hypotheses Testing Results

Hypothesis	Path	β	T-statistic	P-value	Decision
H1	AI → DSD	1.662	13.749	0.000	Accepted
H2	AI → SHRP	0.800	5.017	0.000	Accepted
H3	DSD → SHRP	0.081	1.156	0.248	Rejected

AI = Artificial Intelligence; DSD = Digital Skill Development; SHRP = Sustainable Human Resource Practices

The results strongly support H1, revealing that Artificial Intelligence significantly and positively influences Digital Skill Development, with a large beta coefficient ($\beta = 1.662$) and a t-value of 13.749, well above the critical threshold of 1.96, and a highly significant p-value ($p < 0.001$). This confirms that AI initiatives within Saudi medium-sized enterprises substantially enhance the development of digital competencies among employees. H2 is also accepted, with AI having a significant direct effect on SHRP ($\beta = 0.800$, $t = 5.017$, $p < 0.001$). This indicates that the integration of AI technologies is a key driver in promoting sustainable HR practices, such as fairness, innovation, and social responsibility in HRM systems. However, H3 is rejected, as the relationship between DSD and SHRP was found to be statistically insignificant ($\beta = 0.081$, $t = 1.156$, $p = 0.248$). This suggests that while digital skill development may be conceptually linked to sustainability, it does not independently predict sustainable HR practices in this context. Overall, the findings emphasize the central role of AI in directly shaping both digital capabilities and HR sustainability, while digital skill development alone does not exert a significant standalone effect on SHRP.

The mediation analysis evaluates whether Digital Skill Development (DSD) mediates the relationship between Artificial Intelligence (AI) and Sustainable Human Resource Practices (SHRP). As shown in Figure 7, the model includes the direct path from AI to SHRP and the indirect path through DSD.

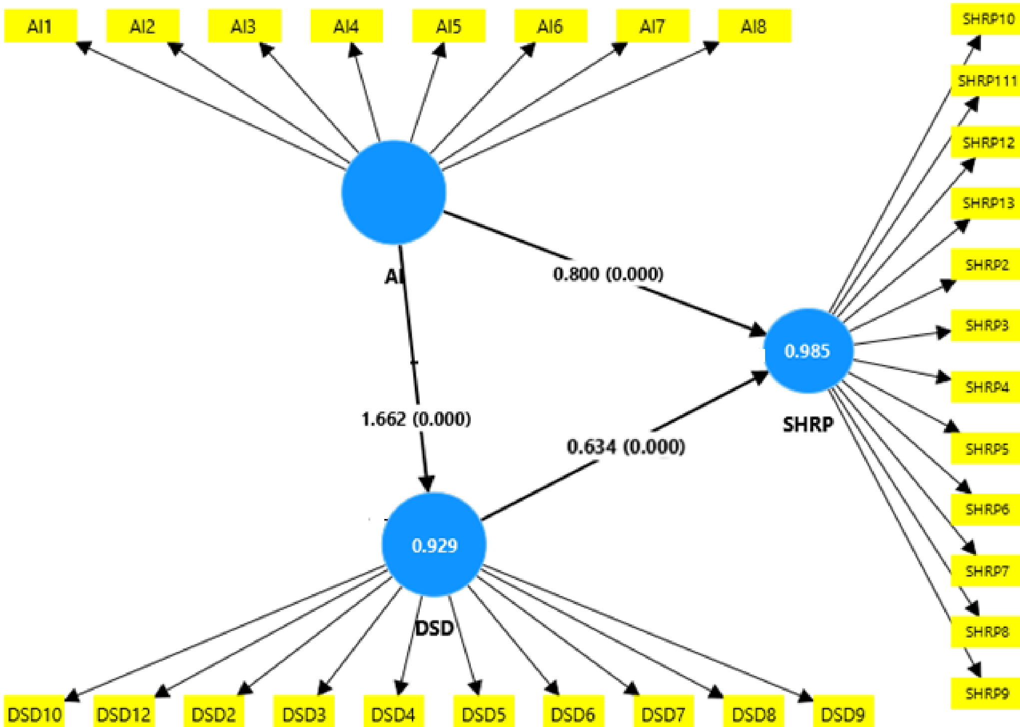

Fig.7: Path Model Results of Mediation

The results demonstrate that AI has a significant direct effect on SHRP (β = 0.800, p = 0.000) and also a significant effect on DSD (β = 1.662, p = 0.000). Furthermore, DSD shows a significant effect on SHRP in this full model (β = 0.634, p = 0.000), suggesting the conditions for partial mediation are met. The presence of both significant direct and indirect effects implies that DSD partially mediates the relationship between AI and SHRP. In practical terms, while AI directly contributes to enhancing sustainable HR practices, it also influences SHRP indirectly by improving the organization's digital skills capacity. This mediation result underscores the importance of developing digital skills as a channel through which AI capabilities are translated into sustainable HR strategies. Organizations aiming to leverage AI for long-term sustainability outcomes should therefore also invest in upskilling their workforce to amplify the benefits of AI integration.

To further validate the mediating role of Digital Skill Development (DSD) between Artificial Intelligence (AI) and Sustainable Human Resource Practices (SHRP), an indirect effect analysis was conducted using bootstrapping in SmartPLS. Table 12 presents the outcome of this mediation test.

Table 11: Indirect Hypothesis

Hypothesis	β	T-statistic	P-value	Decision
H6: AI → DSD → SHRP	0.135	5.870	0.000	Accepted

DSD = Digital Skill Development; SHRP = Sustainable Human Resource Practices

The analysis confirms the significance of the indirect path from AI to SHRP via DSD, with a beta coefficient of 0.135, a T-statistic of 5.870, and a p-value < 0.001. These results strongly support Hypothesis H6, indicating that DSD significantly mediates the relationship between AI and SHRP. This finding suggests that while AI exerts a direct influence on sustainable HR practices, its indirect effect through the enhancement of digital skills is also substantial. The mediation effect confirms the strategic importance of digital upskilling as a pathway through which AI implementation contributes to long-term HR sustainability in Saudi medium-sized enterprises.

5. Discussion

This study set out to explore the influence of Artificial Intelligence (AI) on Sustainable Human Resource Practices (SHRP) within the unique context of Saudi medium-sized enterprises (SMEs), with a particular focus on the mediating role of Digital Skill Development (DSD). As organizations in Saudi Arabia align with the national goals outlined in Vision 2030, there is increasing interest in how technological advancements, particularly AI, can support sustainability-oriented human resource strategies. The findings of this research offer substantial insights into the evolving nature of HRM in digitally transforming economies, especially in emerging markets like Saudi Arabia. The structural model analysis revealed a strong and statistically significant relationship between AI and DSD ($\beta = 1.662$, $p < .001$), suggesting that the adoption of AI systems positively influences the development of digital skills among employees. This outcome resonates with the argument by Dwivedi et al. (2021), who emphasized that AI is not only a tool for automating operational tasks but also a catalyst for organizational learning and digital capability-building. As AI applications such as predictive analytics, chatbot systems, and automated recruitment platforms are integrated into HR functions, employees are required to develop new competencies to interact with these tools (Jarrahi, 2018). Moreover, this finding is consistent with Seker, Kwon, and Kocak (2025) and Agaoglu et al. (2025), who found that AI deployment fosters a culture of continuous learning and digital literacy enhancement, particularly when paired with organizational support systems.

The study also confirmed a significant direct effect of AI on SHRP ($\beta = 0.800$, $p < .001$), indicating that AI-enabled systems enhance sustainable HRM outcomes. This includes improvements in resource efficiency, equitable recruitment practices, transparent performance management, and environmentally conscious HR policies. These results align with previous findings by Alnamrouti, Rjoub, and Ozgit (2022), who concluded that the integration of AI with strategic human resource management facilitates the implementation of sustainability agendas in both governmental and non-governmental sectors. In addition, Budhwar et al. (2023) observed that AI technologies empower HR departments to shift from administrative roles to strategic partners by enabling data-informed decision-making and facilitating long-term workforce planning aligned with corporate sustainability goals. Arsu (2024) further supports this view, asserting that AI adoption within HRM promotes greener organizational practices through automation, better analytics, and optimized employee development programs.

Interestingly, the direct relationship between DSD and SHRP was found to be statistically insignificant ($\beta = 0.081$, $p = .248$). This outcome challenges the commonly held assumption in literature that digital skills directly and significantly contribute to HR sustainability. For instance, while Bondarouk and Brewster (2016) argue that digital competencies are key enablers of innovation and strategic alignment in HR functions, the findings of this study suggest that such skills may not independently result in sustainability outcomes within the Saudi SME context. One plausible explanation is that digital skills alone may not be enough to drive sustainable HR practices unless supported by institutional infrastructure, leadership engagement, and AI system integration. In many Saudi SMEs, strategic decisions remain centralized and top-down, potentially limiting the influence of individual employee competencies on broader HRM strategies (Mahade et al., 2025). This indicates a potential cultural or structural barrier where digital skill development, while present, does not directly translate into impactful HR sustainability unless nested within a larger organizational transformation.

The mediation analysis provided more nuanced insights. The indirect effect of AI on SHRP through DSD was statistically significant ($\beta = 0.135$, $p < .001$), thereby supporting the hypothesis of partial mediation. This finding confirms that while DSD may not directly influence sustainable HR practices, it strengthens the pathway between AI usage and sustainability. In essence, DSD acts as a facilitator helping employees effectively leverage AI tools, which in turn enhances HR outcomes. This finding aligns with the socio-technical systems perspective, which emphasizes that technological change must be complemented by human competence development to produce meaningful organizational outcomes (Faraj, Pachidi, & Sayegh, 2018; Zahoor et al., 2025). Without digital skills, employees may underutilize or misapply AI capabilities, resulting in missed opportunities for sustainability. These results are also consistent with broader discussions in the AI-HRM literature. Budhwar et al. (2023) argue that the integration of AI into HR not only improves process efficiency but also enables the transition toward more strategic and sustainable HR practices. Similarly, Mahade et al. (2025) demonstrate that AI-based HR systems contribute to sustainable performance in higher education institutions by enhancing transparency, decision quality, and employee development. The current findings reinforce these insights by illustrating that AI, when combined with workforce readiness, significantly improves sustainable HR practices.

On the contrary, the non-significant direct effect of DSD on SHRP contrasts with the expectations set by digital transformation literature. Studies such as Vitezić and Perić (2024) and Seker et al. (2025) emphasized the pivotal role of digital literacy in facilitating technology acceptance and innovation in organizations. However, the context of Saudi SMEs might present unique challenges, such as limited autonomy for employees, resource constraints, or underdeveloped digital ecosystems. These contextual factors could explain why digital skills alone were insufficient predictors of sustainable HR outcomes. As Dwivedi et al. (2021) note, findings from Western economies cannot always be generalized to emerging markets, where cultural, economic, and infrastructural dynamics differ markedly. Theoretically, these findings offer strong support for the Resource-Based View (RBV), which posits that organizations achieve sustainable advantage through rare and inimitable internal resources such as AI capabilities and digitally competent employees (Barney, 1991). Yet, this study adds nuance by suggesting that DSD operates more effectively as a strategic enabler rather than a direct predictor of sustainability. Furthermore, the results echo insights from Kowalski et al. (2024), who argue that digital transformation requires the development of microfoundations skills, routines, and knowledge that together support dynamic capabilities. In this regard, AI serves as a driver of change, while DSD enhances the firm’s ability to adapt and evolve HR practices.

From a practical standpoint, the findings suggest that SMEs in Saudi Arabia must view AI adoption and digital skill development as interdependent investments. AI implementation alone may fall short without a digitally literate workforce capable of leveraging its full potential. Managers should therefore integrate

DSD into broader digital transformation strategies, ensuring that training programs align with HR objectives and organizational sustainability goals. Menon et al. (2024) advocate for the strategic integration of analytics and AI in HRM, highlighting that employee development and technological adoption must progress in tandem. For policy-makers, these insights underscore the importance of designing national upskilling programs that cater to SMEs, thereby accelerating their readiness for AI-driven HR modernization and alignment with Vision 2030 objectives.

6. Conclusion

This study set out to investigate the impact of Artificial Intelligence (AI) on Sustainable Human Resource Practices (SHRP) in the context of Saudi medium-sized enterprises, while exploring the mediating role of Digital Skill Development (DSD). Against the backdrop of Saudi Arabia's Vision 2030 and the increasing pressure on organizations to digitize responsibly, this research offers a timely and critical examination of how technological advancements influence HR sustainability and workforce capability. The findings reveal that AI plays a pivotal role in shaping both digital skill development and sustainable HR practices. AI was found to have a strong, statistically significant effect on DSD, confirming that the integration of AI technologies within organizations drives the need for, and supports the development of, new digital competencies. Furthermore, AI was shown to have a direct and substantial impact on SHRP, indicating that technological innovations are not only operational enablers but also strategic tools that enhance transparency, efficiency, inclusivity, and environmental responsibility in HR functions.

Although the study found that DSD did not independently predict SHRP, the mediation analysis confirmed a significant indirect effect, suggesting that digital skills serve to amplify the positive effects of AI on sustainable HRM. This partial mediation highlights the interdependent nature of technology and talent, reinforcing the idea that AI's full potential is realized only when supported by a digitally competent workforce. Theoretically, the study contributes to the existing body of literature by extending socio-technical systems theory and the resource-based view within the context of digital HRM. It provides empirical support for the proposition that AI and digital skills, when aligned strategically, create dynamic capabilities that enhance sustainability. Practically, the study offers valuable insights for HR leaders and policymakers, emphasizing the need to co-invest in AI infrastructure and digital training programs to ensure that technology adoption translates into meaningful and sustainable organizational outcomes. Nonetheless, the study is not without limitations. Its cross-sectional design restricts causal inferences, and the sample was limited to medium-sized enterprises in Saudi Arabia, which may affect the generalizability of the findings. Future research could adopt longitudinal designs, expand the scope to include large or small enterprises, or explore cross-cultural comparisons to build a more comprehensive understanding of how AI and digital skill development influence sustainable HR practices globally.

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