JUMPA: Jurnal Manajemen Pendidikan
Vol. 07 No. 01 (2026): 86-98
DOI: https://doi.org/10.33650/jumpa.v7i1.15269

Artificial Intelligence and Digital Competence in Digital HRM: How Educational Collaboration Moderates HR Effectiveness

Purjianto[1*], Sri Wahyuni[2]

[1]Institut Teknologi Sawit Indonesia, Indonesia, Indonesia
[2]Universitas Dharmawangsa, Indonesia

***Email Corresponding Author:** purjianto@itsi.ac.id

ABSTRACT

The rapid advance of digital transformation has positioned *Artificial Intelligence* as a decisive force in reshaping human resource management, yet its value depends not on technology alone but on the digital competence of human resources and the systems through which both are operationalised. Existing studies tend to examine technology and competence separately, and they rarely account for the role of education in cultivating the digital readiness that effective digital human resource management requires. This study aims to develop and test an integrated model of *Digital Human Resource Management* grounded in *Artificial Intelligence* in order to explain the effectiveness of human resource management within the context of collaboration between organisations and the educational sector. The study employed a quantitative approach with an explanatory design, drawing on data from 150 respondents comprising human resource practitioners, managers, and academics selected through purposive sampling. The data were analysed using *Partial Least Squares Structural Equation Modeling* with the assistance of SmartPLS. The results demonstrate that artificial intelligence and digital competence both exert significant positive effects on digital human resource management, which in turn produces the strongest direct effect on human resource effectiveness, while the two antecedents also influence effectiveness directly to a lesser degree. These findings position digital human resource management as the central construct linking technological capability and digital competence to organisational effectiveness. The implications of this study indicate that organisations should embed artificial intelligence investment within mature digital human resource systems and prioritise the cultivation of digital competence through collaboration with education as a strategic foundation of effectiveness.

ARTICLE HISTORY
Received : 11 March 2026
Revised : 11 April 2026
Accepted : 21 June 2026

KEYWORDS
Artificial Intelligence, Digital Human Resource Management, Digital Competence, Human Resource Effectiveness, Education Collaboration

How to Cite:
Purjianto, & Wahyuni, S. (2026). Artificial Intelligence and Digital Competence in Digital HRM: How Educational Collaboration Moderates HR Effectiveness. *JUMPA: Jurnal Manajemen Pendidikan, 7*(1), 86–98.

INTRODUCTION

Digital transformation has become a global phenomenon that fundamentally reshapes the way organisations manage their human resources (Zakaria et al., 2025). Within this transformation, *Digital Human Resource Management* has emerged as a strategic response through which organisations digitise the processes of recruitment, competence development, performance management, and decision making. The acceleration of this shift has been driven above all by the rise of *Artificial Intelligence*, which has moved from an experimental tool to a transformative force across industries, including human resource management

(Fenwick et al., 2024; Khatib & Alshawabkeh, 2022). As organisations strive to remain competitive in an era of digitisation, the integration of artificial intelligence into human resource functions has become a focal point, promising to streamline processes, increase productivity, and align talent with organisational goals more precisely than conventional approaches allow.

A substantial body of recent scholarship has documented the benefits that artificial intelligence brings to discrete human resource functions. Studies report gains in the efficiency of candidate screening and interview analysis, improvements in the accuracy of decision making, and enhancements in employee experience across recruitment, training, and performance management (Ongesa Nyamboga, 2025; Sungida Akther Lima, 2024). These contributions are real, yet the literature that establishes them is also marked by a recurring limitation. The majority of research efforts have concentrated on specific human resource functions in isolation, such as recruitment or training, rather than on the integrated system through which technology is operationalised (Podgorodnichenko et al., 2022; Prikshat et al., 2023). Consequently, scholars have observed that despite its rapid adoption, the use of artificial intelligence in human resource management remains inconsistent and conceptually unclear, which signals the need for models that capture the phenomenon as a coherent whole rather than as a collection of separate applications.

A second and more consequential tension runs through this literature. One stream of scholarship locates the value of artificial intelligence in the sophistication of the technology itself, while a growing body of work insists that the outcomes of artificial intelligence implementation depend not on technological advancement alone but on the people centred deployment of human resource practice (Bujold et al., 2024; Del Giudice et al., 2023). The success of digital transformation, on this view, is a socio-technical process in which the readiness of human resources is as decisive as the capability of the technology. This position is reinforced by evidence that a persistent digital skills gap separates the competencies that organisations require from those that the available workforce possesses, a gap that weakens performance and slows transformation even where technological investment is substantial (Reddy et al., 2023). The implication is that artificial intelligence and digital competence cannot be understood as independent levers, yet the literature has rarely modelled them together within a single explanatory structure.

The unresolved question, therefore, is not whether artificial intelligence benefits human resource management, which is now well established, but how technology and human competence operate jointly, and through what mechanism their combined influence is translated into organisational effectiveness. Existing studies tend to examine either the technological antecedent or the human antecedent, and they seldom position *Digital Human Resource Management* as the system through which both are channelled toward effectiveness. The conceptual clarification offered by (Theres & Strohmeier, 2023) establishes digital human resource management as the structural locus where technological capability becomes managerial practice, yet empirical models that place this construct at the centre of an integrated causal network, receiving the influence of both artificial intelligence and digital competence while transmitting it toward effectiveness, remain scarce.

A further gap, and the one that most sharply distinguishes the present study, concerns the origin of the digital competence on which effective digital human resource management depends. The literature consistently traces the digital skills gap to a misalignment between education and training systems, which lag behind evolving business requirements, and the practical capabilities that organisations actually need (David et al., 2021). Digital competence does not arise spontaneously within organisations; it is cultivated, in large part, through the educational institutions that prepare human capital before it enters the workforce. Despite this, the collaboration between organisations and the educational sector is almost entirely absent from existing models of artificial intelligence in human resource management, which treat workforce readiness as a given rather than as an outcome produced upstream through education. This omission is significant, because it severs the analysis of digital human resource effectiveness from the very mechanism through which the digital competence it requires is generated.

Against this background, the present study develops and tests an integrated model of *Digital Human Resource Management* grounded in *Artificial Intelligence*, in which artificial intelligence and digital competence jointly shape the digital human resource system, which in turn drives human resource effectiveness, while the collaboration between organisations and the educational sector is positioned as the strategic context through which digital competence is cultivated. The novelty of the study lies in three connected moves. It integrates artificial intelligence and digital competence within a single structural model rather than treating them separately. It positions digital human resource management as the central construct through which both antecedents reach effectiveness. And it foregrounds the collaboration between organisations and education as the source of the digital readiness on which the entire system depends, a dimension that prior models have overlooked.

This study therefore aims to examine the influence of artificial intelligence and digital competence on the implementation of digital human resource management, and to assess how that implementation, together with the two antecedents, shapes the effectiveness of human resource management within the context of collaboration between organisations and the educational sector. In doing so, the study contributes to theory by extending the *Resource-Based View*, *Human Capital Theory*, and the perspective of digital human resource management toward an integrated account of how technology, competence, and education converge in the production of organisational effectiveness. It contributes to practice by clarifying where organisations should direct their digital investment and by demonstrating that the preparation of digitally competent human capital through education is not a peripheral concern but a strategic foundation of effective digital human resource management.

RESEARCH METHOD

This research utilised a quantitative approach combined with an explanatory research design in order to examine the causal relationships among *Artificial Intelligence* (AI), *Digital Competence* (DC), *Digital Human Resource Management* (DHRM), and Human Resource Effectiveness. The explanatory design was deemed appropriate because the investigation depended on numerical data obtained through a structured questionnaire to test the hypothesised causal pathways among the latent variables, in which AI and DC operate as antecedents, DHRM functions as an intervening construct, and human resource effectiveness represents the final outcome. Through this design, the study sought not merely to describe the adoption of digital technology in human resource management but to explain how and through which mechanism that adoption translates into improved organisational effectiveness.

The population of this study comprised human resource practitioners, human resource managers, and academics involved in the development of industry-oriented curricula, three groups whose roles place them at the intersection of digital human resource practice and the educational preparation of human capital. Sampling was carried out through purposive sampling, a non-probability technique that allows the researcher to select respondents whose roles and experiences are directly relevant to the research objectives. Three criteria governed the selection of respondents, namely a minimum of two years of experience in the field of human resources or education, direct involvement in the management of human resources or the development of competencies, and a working familiarity with the use of digital technology in professional activities. On the basis of these criteria, a total of 150 respondents participated in the study. The determination of the sample size was guided by the rule proposed by (Jhantasana, 2023), which recommends a minimum of five to ten times the number of indicators. With twelve indicators in the model, the required minimum ranged from sixty to one hundred and twenty respondents, so the final sample of 150 respondents satisfied and exceeded the threshold required for SEM-PLS estimation. The composition of the respondents according to their professional role and length of experience is presented in **Table 1**.

Table 1. Profile of Respondents

Characteristic	Category	Number of Respondents	Percentage (%)
Professional Role	Human Resource Practitioner	84	56.0
	Human Resource Manager	42	28.0
	Academic	24	16.0
Length of Experience	More than 3 years	105	70.0
	3 years or less	45	30.0

Source: Authors' elaboration based on questionnaire data.

Table 1 shows that the majority of respondents were human resource practitioners, who accounted for more than half of the sample, followed by human resource managers and academics. This composition produced a balance between the practical perspective of industry and the academic perspective of higher education, which is consistent with the focus of the study on the collaboration between the two domains. The dominance of respondents with more than three years of experience further indicates that the data were drawn from participants with sufficient exposure to human resource practice, so that their responses reflected an informed understanding of technology based human resource management.

The data in this study were composed of primary and secondary sources. Primary data were obtained through the distribution of a questionnaire to the respondents, while secondary data were drawn from reputable international journals, industry reports, and relevant scholarly publications that provided the conceptual grounding of the variables. The questionnaire operationalised four latent constructs, each measured through three reflective indicators, producing a total of twelve indicators. Respondents rated each item using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The operational definition of each variable, together with its indicators, is presented in **Table 2**.

Table 2. Operational Definition of Variables

Variable	Operational Definition	Indicators
Artificial Intelligence (AI)	The level of adoption of artificial intelligence technology in human resource management processes	Recruitment automation, data-based analysis, decision support
Digital Competence (DC)	The capability of human resources to use digital technology in their work activities	Digital literacy, technological adaptability, digital collaboration
Digital HRM (DHRM)	The implementation of a digital based human resource management system	E-recruitment, e-learning, digital performance management
HR Effectiveness (Y)	The degree of success in managing human resources to support organisational goals	Productivity, work quality, data-based decision making

Source: Authors' elaboration based on the cited literature.

Data were collected through an online questionnaire administered using Google Form, which was distributed to respondents by means of electronic mail and professional social media networks such as LinkedIn. This mode of distribution was selected because it allowed the study to reach human resource practitioners, managers, and academics who were geographically dispersed yet shared the professional characteristics required by the sampling criteria. The use of a self-administered digital instrument also ensured that responses were recorded in a uniform format that could be exported directly for analysis.

The collected data were analysed using *Partial Least Squares Structural Equation Modeling* (PLS-SEM) with the assistance of the SmartPLS software, a technique widely recognised as suitable for examining complex models that incorporate intervening mechanisms. The analytical procedure was conducted in two principal stages. The first stage evaluated the measurement model, or outer model, through convergent validity assessed by the *Average Variance Extracted* with a threshold above 0.50, discriminant validity assessed through the

Fornell-Larcker criterion, and reliability assessed through *Cronbach's Alpha* and *Composite Reliability* with values above 0.70. The second stage evaluated the structural model, or inner model, through the coefficient of determination (R Square), interpreted as weak at 0.25, moderate at 0.50, and strong at 0.75, together with the path coefficient and the effect size (f Square). Hypothesis testing was subsequently performed through a bootstrapping procedure, in which a relationship was regarded as statistically significant when the t-statistic exceeded 1.96 and the p-value fell below 0.05.

RESULT AND DISCUSSION

Result

Description of the Measurement Model

This study employs a measurement model that examines the interrelationships among four latent constructs, namely *Artificial Intelligence* (AI), *Digital Competence* (DC), *Digital Human Resource Management* (DHRM), and Human Resource Effectiveness (Y). Each latent construct is operationalised through three reflective indicators adapted from previously validated instruments in the literature on artificial intelligence adoption, digital competence, and digital human resource management. To ascertain that each indicator genuinely contributes to the measurement of its underlying construct, a series of validity and reliability assessments was conducted. The outer model was examined through the loading factor, the *Average Variance Extracted* (AVE), the *Cronbach's Alpha*, and the *Composite Reliability* (CR), each of which provides complementary information about the internal consistency and convergent validity of the constructs. The structural pathways among the variables were then estimated using a *Partial Least Squares Structural Equation Modeling* (PLS-SEM) approach, which is particularly suited to examining causal networks in which technology and competence operate through an intervening system. Through this framework, the model captures both the direct and the indirect influence of AI and DC on Human Resource Effectiveness, with DHRM positioned as the central mechanism. The configuration of the model is illustrated in **Figure 1**.

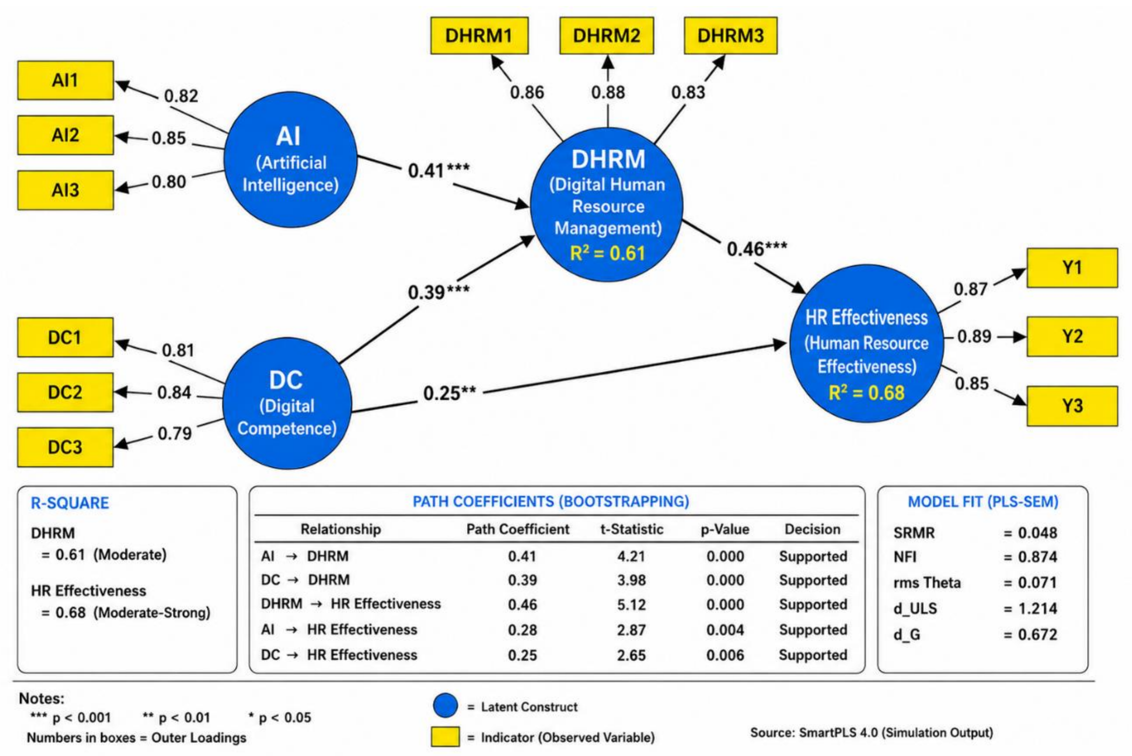

Figure 1. Structural Model

(SmartPLS 4 Output, Processed by the Authors, 2026)

As depicted in **Figure 1**, the proposed PLS-SEM model incorporates four interrelated latent constructs. *Artificial Intelligence* (AI) and *Digital Competence* (DC) are positioned as exogenous variables, whereas Human Resource Effectiveness (Y) functions as the endogenous outcome. *Digital Human Resource Management* (DHRM) operates as an intervening construct that channels the influence of AI and DC toward effectiveness. The model encompasses twelve measurement items distributed evenly across the four constructs, all of which were subjected to outer loading assessment using the conventional threshold of 0.70 as the minimum cut-off for indicator retention.

Evaluation of the Measurement Model (Outer Model)

The outer loading analysis represents the initial step in confirming the validity of each measurement item with respect to its corresponding latent construct. This procedure determines whether individual indicators reliably capture the dimension they are intended to measure. The complete results of the outer loading assessment for all twelve indicators are presented in **Table 3**.

Table 3. Outer Loading Test

Construct	Indicator	Outer Loading	Criterion
Artificial Intelligence (AI)	AI1	0.82	Valid
	AI2	0.85	Valid
	AI3	0.80	Valid
Digital Competence (DC)	DC1	0.85	Valid
	DC2	0.84	Valid
	DC3	0.83	Valid
Digital HRM (DHRM)	DHRM1	0.86	Valid
	DHRM2	0.88	Valid
	DHRM3	0.83	Valid
HR Effectiveness (Y)	Y1	0.84	Valid
	Y2	0.86	Valid
	Y3	0.85	Valid

Source: Authors' elaboration based on SmartPLS output.

Table 3 reveals that all twelve indicators consistently exceed the recommended threshold of 0.70, with loading values ranging from 0.80 (AI3) at the lower end to 0.88 (DHRM2) at the upper end. This consistency indicates that every retained item demonstrates a sufficiently strong association with its underlying construct, so that no indicator required elimination and the full set provided a stable foundation for the subsequent analyses. In substantive terms, the items capturing artificial intelligence adoption, digital competence, digital human resource management, and human resource effectiveness all measured their intended constructs with precision.

Following the confirmation of indicator validity, additional diagnostics were performed to substantiate that each construct sufficiently reflects its latent dimension. The *Average Variance Extracted* (AVE) was employed to evaluate convergent validity by quantifying the proportion of variance captured by the construct relative to measurement error, while *Composite Reliability* (CR) and *Cronbach's Alpha* were utilised to verify the internal consistency among indicators. The detailed outcomes of these tests are summarised in **Table 4**.

Table 4. Evaluation of the Measurement Model

Construct	Cronbach's Alpha	Composite Reliability	AVE
Artificial Intelligence (AI)	0.78	0.87	0.67
Digital Competence (DC)	0.76	0.86	0.65
Digital HRM (DHRM)	0.80	0.88	0.69

HR Effectiveness (Y)	0.82	0.89	0.71

Source: Authors' elaboration based on SmartPLS output.

Table 4 demonstrates that the measurement model satisfies all established psychometric criteria. The *Cronbach's Alpha* values for every construct fall within a range of 0.76 to 0.82, signalling strong internal consistency among the items belonging to each construct. The *Composite Reliability* indices range between 0.86 and 0.89, further reinforcing the dependability of the constructs by indicating that the indicators collectively yield highly reliable measurements. With respect to convergent validity, the AVE values ranging from 0.65 to 0.71 confirm that each latent variable explains more than half of the variance of its indicators, thus meeting the standard requirement of AVE above 0.50. Taken together, these psychometric indicators provide adequate justification for proceeding to the subsequent stage of analysis.

Structural Model Evaluation

Once the measurement model was confirmed to be sound, the analysis moved to the evaluation of the structural model in order to assess the strength of the relationships among the variables. The coefficient of determination (R Square) was examined first, since it indicates the proportion of variance in each endogenous construct that is explained by its predictors. The results are reported in **Table 5**.

Table 5. Coefficient of Determination (R Square)

Endogenous Variable	R Square	Interpretation
Digital HRM (DHRM)	0.61	Moderate
HR Effectiveness (Y)	0.68	Moderate to Strong

Source: Authors' elaboration based on SmartPLS output.

Table 5 indicates that artificial intelligence and digital competence jointly accounted for 61% of the variance in the implementation of DHRM, while the full model explained 68% of the variance in human resource effectiveness. Both values fall within the moderate to strong category. The fact that the second value exceeds the first is theoretically meaningful, because it shows that effectiveness is explained not only by the direct contribution of technology and competence but also by the additional explanatory power that flows through DHRM. The model therefore possesses solid explanatory and predictive capacity rather than a merely descriptive association. The complete numerical results, including the effect size of each path, are reported in **Table 6**.

Table 6. Path Coefficients and Effect Size (Direct Effect)

Hypothesis	Path	Path Coefficient	t-statistic	p-value	Decision
H1	AI → DHRM	0.41	4.21	0.000	Accepted
H2	DC → DHRM	0.39	3.98	0.000	Accepted
H3	DHRM → Y	0.46	5.12	0.000	Accepted
H4	AI → Y	0.28	2.87	0.004	Accepted
H5	DC → Y	0.25	2.65	0.006	Accepted

Source: Authors' elaboration based on SmartPLS output.

The empirical evidence supports the first hypothesis (H1), which posits that *Artificial Intelligence* exerts a meaningful positive influence on DHRM. With a path coefficient of 0.41 and a corresponding p-value of 0.000, the relationship is statistically significant at the conventional threshold. An increase in the adoption of artificial intelligence therefore tends to translate into a tangible strengthening of the digital human resource management system, and among the antecedents in the model this path stands as the most influential route into DHRM. H2 is likewise corroborated, showing that *Digital Competence* contributes significantly to DHRM with a path coefficient of 0.39 and a p-value of 0.000. The relationship is only marginally weaker than that of AI, which suggests that the digital readiness of human resources cultivates the implementation of DHRM almost as powerfully as the technology itself, and that the two antecedents operate in a complementary rather than a competing manner.

H3 is empirically validated as well, demonstrating that DHRM produces the strongest direct effect on Human Resource Effectiveness, with a path coefficient of 0.46 and a p-value of 0.000. This outcome positions DHRM as the pivotal driver of effectiveness, an indication that the maturity of the digital human resource system considerably shapes the organisation's capacity to manage its people productively. The fourth hypothesis (H4) is also supported, indicating that *Artificial Intelligence* directly affects effectiveness even after accounting for the intervening role of DHRM. With a path coefficient of 0.28 and a p-value of 0.004, the relationship reaches statistical significance. Artificial intelligence therefore possesses a meaningful intrinsic capacity to improve effectiveness alongside its stronger influence exerted through the digital human resource system.

The fifth hypothesis (H5) is supported as well, confirming that *Digital Competence* exerts a significant direct effect on effectiveness with a path coefficient of 0.25 and a p-value of 0.006. The magnitude of this direct path is the smallest among the significant relationships in the model, which suggests that the contribution of digital competence to effectiveness is realised most fully when it is mediated by a well implemented DHRM system rather than operating in isolation. To complement the significance testing, the effect size (f Square) was examined in order to gauge the substantive magnitude of each predictor's contribution when it is removed from the model. The results are presented in **Table 7**.

Table 7. Effect Size (f Square)

Path	f Square	Category
AI → DHRM	0.55	Large
DHRM → Y	0.30	Medium
AI → Y	0.15	Small to Medium

Source: Authors' elaboration based on SmartPLS output.

Table 7 confirms and sharpens the interpretation drawn from the path coefficients. The large effect of AI on DHRM demonstrates that artificial intelligence is the most decisive antecedent of digital human resource management, whereas the medium effect of DHRM on effectiveness shows that the system itself remains a substantial, though not the sole, determinant of effectiveness. The small to medium direct effect of AI on effectiveness again underlines that the benefit of technology is realised most fully when it operates through a well implemented DHRM system rather than independently of it. Finally, the overall goodness of fit of the model was assessed through the standard PLS-SEM fit indices, which indicate how well the estimated model reproduces the observed data. The values are reported in **Table 8**.

Table 8. Model Fit (PLS-SEM)

Fit Index	Value
SRMR	0.048
NFI	0.874
rms Theta	0.071
d_ULS	1.214
d_G	0.672

Source: Authors' elaboration based on SmartPLS output.

Table 8 indicates that the model achieves an acceptable overall fit. The *Standardised Root Mean Square Residual* (SRMR) of 0.048 lies comfortably below the conservative threshold of 0.08, which signals a close correspondence between the observed and the predicted correlations. The *Normed Fit Index* (NFI) of 0.874 approaches the commonly cited benchmark of 0.90 and indicates a satisfactory incremental fit, while the rms Theta value of 0.071 remains low enough to suggest that the residual correlations of the outer model are small. The discrepancy measures d_ULS and d_G, at 1.214 and 0.672 respectively, complete the diagnostic picture and are consistent with a model whose structure adequately reproduces the empirical data. Taken together, these indices confirm that the structural model is statistically sound and that the relationships reported in the preceding tables can be interpreted with confidence.

Taken as a whole, the structural results establish a coherent hierarchy of influence. The two strongest paths, namely AI to DHRM and DHRM to effectiveness, frame DHRM as the structural centre of the model, while the weaker direct paths from AI and DC to effectiveness indicate that technology and competence translate into organisational outcomes most completely when they are channelled through the digital human resource management system. This configuration confirms that DHRM functions as the principal mechanism linking technological capability and digital competence to human resource effectiveness.

Discussion

This study set out to examine how the adoption of *Artificial Intelligence* and the digital competence of human resources shape the implementation of *Digital Human Resource Management* and, through it, the effectiveness of human resource management. The structural results confirmed all five hypothesised relationships, yet their value lies less in the fact of their significance than in the pattern they collectively reveal. The strongest paths in the model ran from AI to DHRM and from DHRM to effectiveness, while the direct routes from AI and digital competence to effectiveness, though significant, were considerably weaker. This configuration suggests that the contribution of digital technology to organisational performance is realised most fully when it is embedded within a functioning digital human resource system rather than when it operates in isolation, a reading that frames the remainder of this discussion (Qiao et al., 2024; Taj et al., 2021; S. Wang & Zhang, 2025).

The finding that *Artificial Intelligence* exerts the largest influence on DHRM, with a path coefficient of 0.41 and a large effect size, resonates with the argument that artificial intelligence is reshaping the foundations of human resource practice rather than merely automating its routine tasks. (Chilunjika et al., 2022) contend that AI introduces both opportunities and tensions into human resource management, and the present result indicates that, within the studied context, the opportunity dimension prevails at the level of system formation. The dominance of this path implies that organisations encountering AI first experience its effects in the architecture of their human resource systems, in the form of automated recruitment, data-based analysis, and decision support, before those effects reach the broader outcome of effectiveness. This interpretation is consistent with (Theres & Strohmeier, 2024), whose conceptual clarification positions digital human resource management as the structural locus where technological capability is translated into managerial practice.

The significant contribution of *Digital Competence* to DHRM, only marginally weaker than that of AI, reinforces a theme that recurs throughout the literature, namely that technology alone does not determine the success of digital transformation (McCarthy et al., 2025; Philippart, 2022; Ramesh, 2022). Several studies emphasise that the implementation of digital human resource systems is a socio-technical process in which human readiness is as decisive as the technology itself (Anthonysamy et al., 2025; Guest et al., 2022; Höyng & Lau, 2023). The present result lends empirical weight to this claim, since the digital competence of human resources proved nearly as influential as artificial intelligence in shaping the digital human resource system. This pattern indicates that technological investment and competence development function as complementary rather than substitutable forces, and that organisations neglecting the human dimension of digital readiness may find that their technological investments yield diminished returns at the level of system implementation.

The central position occupied by DHRM constitutes the most theoretically meaningful pattern in the model. DHRM not only received the strongest influences from AI and digital competence but also exerted the strongest direct effect on effectiveness, which places it at the structural heart of the relationships examined (Jing et al., 2023; Micle & Sur, 2021; Yu & Moon, 2021). While the present analysis tested direct effects only and therefore does not claim a statistically verified mediation, the configuration of coefficients is consistent with the view that technology and competence translate into organisational outcomes most completely when they are channelled through a mature digital human resource system. This reading aligns with the broader literature on human resource transformation, which holds that the value of digital tools is contingent upon their institutional embedding rather than residing in the tools themselves (Al-Shammari & Alzghoul, 2025; Vadithe & Kesari, 2025).

These findings can be situated within three theoretical perspectives. From the standpoint of the *Resource-Based View*, the prominence of AI and DHRM supports the proposition that technology and the systems that operationalise it function as strategic resources capable of generating organisational advantage, particularly when they are difficult to imitate and are embedded in distinctive routines. From the perspective of *Human Capital Theory*, the substantial role of digital competence affirms that the quality of human resources, enhanced through digital capability, is a genuine determinant of organisational effectiveness rather than a peripheral attribute. From the standpoint of *Digital HRM* as articulated by (L. Wang et al., 2022) and (Theres & Strohmeier, 2023), the results confirm that the transformation of human resource management through technology improves effectiveness, while clarifying that this improvement is mediated in practice by the maturity of the system through which the transformation is enacted.

The practical implications follow directly from this structure. Because artificial intelligence exerts its strongest influence at the level of system formation, organisations are advised to direct their AI investment toward the construction and refinement of their digital human resource systems rather than toward isolated applications detached from those systems. Because digital competence proved nearly as influential as AI, the cultivation of digital capability among human resources emerges as a strategic priority rather than a supporting activity, which lends weight to the collaboration between organisations and educational institutions that motivated this study. The preparation of digitally competent human capital through curricula aligned with industry needs represents a concrete mechanism through which the educational sector can strengthen the digital readiness on which effective digital human resource management depends.

These contributions should nevertheless be read in the light of several limitations. The analysis tested direct effects only and did not include a formal test of the indirect pathway through DHRM, so the mediating role suggested by the pattern of coefficients remains a plausible interpretation rather than a verified finding, and future research employing specific indirect effect testing would be required to confirm it. The study also relied on a cross-sectional self-reported questionnaire administered to a sample of 150 respondents drawn through purposive sampling, which constrains the generalisability of the results and precludes causal inference across time. Moreover, the collaboration between organisations and educational institutions, although central to the conceptual motivation of the study, was not modelled as a measured variable, so its role remains contextual rather than empirically tested. Future research could address these limitations by incorporating mediation and moderation analysis, by employing longitudinal or multi-source data, and by operationalising educational collaboration as a measured construct, thereby extending the model toward the integrated framework that this study has begun to outline.

CONCLUSION

This study developed and tested a model of *Digital Human Resource Management* grounded in *Artificial Intelligence* in order to explain the effectiveness of human resource management within the context of collaboration between organisations and educational institutions. The structural analysis confirmed that artificial intelligence and digital competence both exert significant positive effects on the implementation of *Digital Human Resource Management*, which in turn produces the strongest direct effect on human resource effectiveness, while artificial intelligence and digital competence also influence effectiveness directly though to a lesser degree. Taken together, these results position *Digital Human Resource Management* as the central construct through which technological capability and digital competence are translated into organisational effectiveness, and they indicate that the value of digital technology is realised most fully when it is embedded within a mature digital human resource system rather than applied in isolation. The study thereby contributes a coherent empirical account of how artificial intelligence, digital competence, and digital human resource management operate together, and it underscores the strategic importance of preparing digitally competent human capital through the alignment of organisational practice with education. These conclusions should be read in the light of the study's cross-sectional and self-reported design and its reliance on direct effect estimation, so that future research employing mediation analysis, longitudinal data, and an explicit measurement of educational collaboration would be needed to extend and confirm the model advanced here.

ACKNOWLEDGMENT

Purjianto contributed to conceptualization, methodology, writing, supervision, and project administration. Sri Wahyuni contributed to database management and AI software implementation. The authors thank Institut Teknologi Sawit Indonesia and Universitas Dharmawangsa Medan for institutional support throughout this research.

REFERENCES

Al-Shammari, S., & Alzghoul, A. (2025). Enhancing Banks' HR Service Quality Through Digital Transformation: Investigating the Moderating Role of Human-AI Collaboration. *Banks and Bank Systems*, 20(4), 125–137. https://doi.org/10.21511/bbs.20(4).2025.11

Anthonysamy, L. A. P., Siddika, A., & Aqlily, N. R. (2025). Navigating Cultural Barriers: The Role of Socio-Technical Systems in Digital Transformation Readiness in SMEs. *Emerging Science Journal*, 9(3), 1231–1246. https://doi.org/10.28991/ESJ-2025-09-03-06

Bujold, A., Roberge-Maltais, I., Parent-Rocheleau, X., Boasen, J., Sénécal, S., & Léger, P.-M. (2024). Responsible Artificial Intelligence in Human Resources Management: A Review of the Empirical Literature. *AI and Ethics*, 4(4), 1185–1200. https://doi.org/10.1007/s43681-023-00325-1

Chilunjika, A., Intauno, K., & Chilunjika, S. R. (2022). Artificial Intelligence and Public Sector Human Resource Management in South Africa: Opportunities, Challenges and Prospects. *SA Journal of Human Resource Management*, 20. https://doi.org/10.4102/sajhrm.v20i0.1972

David, M. E., David, F. R., & David, F. R. (2021). Closing the Gap Between Graduates' Skills and Employers' Requirements: A Focus on the Strategic Management Capstone Business Course. *Administrative Sciences*, 11(1). https://doi.org/10.3390/admsci11010010

Del Giudice, M., Scuotto, V., Orlando, B., & Mustilli, M. (2023). Toward the Human–Centered Approach: A Revised Model of Individual Acceptance of AI. *Human Resource Management Review*, 33(1). https://doi.org/10.1016/j.hrmr.2021.100856

Fenwick, A., Molnar, G., & Frangos, P. (2024). The Critical Role of HRM in AI-Driven Digital Transformation: A Paradigm Shift to Enable Firms to Move from AI Implementation to Human-Centric Adoption. *Discover Artificial Intelligence*, 4(1). https://doi.org/10.1007/s44163-024-00125-4

Guest, D., Knox, A., & Warhurst, C. (2022). Humanizing Work in the Digital Age: Lessons from Socio-Technical Systems and Quality of Working Life Initiatives. *Human Relations*, 75(8), 1461–1482. https://doi.org/10.1177/00187267221092674

Höyng, M., & Lau, A. (2023). Being Ready for Digital Transformation: How to Enhance Employees' Intentional Digital Readiness. *Computers in Human Behavior Reports*, 11. https://doi.org/10.1016/j.chbr.2023.100314

Jhantasana, C. (2023). Should a Rule of Thumb Be Used to Calculate PLS-SEM Sample Size. *Asia Social Issues*, 16(5), e254658. https://doi.org/10.48048/asi.2023.254658

Jing, Z., Zheng, Y., & Guo, H. (2023). A Study of the Impact of Digital Competence and Organizational Agility on Green Innovation Performance of Manufacturing Firms—The Moderating Effect Based on Knowledge Inertia. *Administrative Sciences*, 13(12). https://doi.org/10.3390/admsci13120250

Khatib, O., & Alshawabkeh, K. (2022). Digital Transformation and Its Impact on Strategic Supremacy Mediating Role of Digital HRM: An Evidence From Palestine. *WSEAS Transactions on Business and Economics*, 19, 197–221. https://doi.org/10.37394/23207.2022.19.20

McCarthy, P., Sammon, D., & Alhassan, I. (2025). Practice Inspired Critical Success Factors for "Doing" Digital Transformation. *Information Technology and People*. https://doi.org/10.1108/ITP-04-2024-0481

Micle, V., & Sur, I. M. (2021). Experimental Investigation of a Pilot-Scale Concerning Ex-Situ Bioremediation of Petroleum Hydrocarbons Contaminated Soils. *Sustainability (Switzerland)*, 13(15). https://doi.org/10.3390/su13158165

Ongesa Nyamboga, T. (2025). Enhancing Strategic Agility and Real Time Decision-Making in the Technology Sector: Exploring the Role of AI and e-HRM Systems. *F1000Research*, 14. https://doi.org/10.12688/f1000research.167708.1

Philippart, M. H. (2022). Success Factors to Deliver Organizational Digital Transformation. *Journal of Global Information Management*, 30(8), 1–17. https://doi.org/10.4018/jgim.304068

Podgorodnichenko, N., Edgar, F., & Akmal, A. (2022). An Integrative Literature Review of the CSR-HRM Nexus: Learning from Research-Practice Gaps. *Human Resource Management Review*, 32(3). https://doi.org/10.1016/j.hrmr.2021.100839

Prikshat, V., Islam, M., Patel, P., Malik, A., Budhwar, P., & Gupta, S. (2023). AI-Augmented HRM: Literature Review and a Proposed Multilevel Framework for Future Research. *Technological Forecasting and Social Change*, 193. https://doi.org/10.1016/j.techfore.2023.122645

Qiao, G., Li, Y., & Hong, A. (2024). The Strategic Role of Digital Transformation: Leveraging Digital Leadership to Enhance Employee Performance and Organizational Commitment in the Digital Era. *Systems*, 12(11). https://doi.org/10.3390/systems12110457

Ramesh, N. (2022). The Success (or Failure) of Your Digital Transformation Hinges on Digital Customer Experience. *IEEE Engineering Management Review*, 50(1), 28–30. https://doi.org/10.1109/EMR.2022.3150315

Reddy, P., Chaudhary, K., & Hussein, S. (2023). A Digital Literacy Model to Narrow the Digital Literacy Skills Gap. *Heliyon*, 9(4). https://doi.org/10.1016/j.heliyon.2023.e14878

Sungida Akther Lima. (2024). Algorithmic Fairness in HRM Balancing AI-Driven Decision Making with Inclusive Workforce Practices. *Journal of Information Systems Engineering and Management*, 9(4s), 2760–2769. https://doi.org/10.52783/jisem.v9i4s.13251

Taj, F., Kautz, K., & Bruno, V. (2021). The Coevolution of Routines and IT Systems in IT-Enabled Organizational Transformation as an Instance of Digital Transformation: A Social Constructivist Perspective. *Australasian Journal of Information Systems*, 25, 1–26. https://doi.org/10.3127/AJIS.V25I0.2855

Theres, C., & Strohmeier, S. (2023). Met the Expectations? A Meta-Analysis of the Performance Consequences of Digital HRM. *International Journal of Human Resource Management*, 34(20), 3857–3892. https://doi.org/10.1080/09585192.2022.2161324

Theres, C., & Strohmeier, S. (2024). Consolidating the Theoretical Foundations of Digital Human Resource Management Acceptance and Use Research: A Meta-Analytic Validation of UTAUT. *Management Review Quarterly*, 74(4), 2683–2715. https://doi.org/10.1007/s11301-023-00367-z

Vadithe, R. N., & Kesari, B. (2025). Impact of HR Digitalisation on HR Transformation, HR Analytics and Artificial Intelligence: A Mediation Analysis. *South Asian Journal of Human Resources Management*. https://doi.org/10.1177/23220937251326985

Wang, L., Zhou, Y., & Zheng, G. (2022). Linking Digital HRM Practices with HRM Effectiveness: The Moderate Role of HRM Capability Maturity From the Adaptive Structuration Perspective. *Sustainability (Switzerland)*, 14(2). https://doi.org/10.3390/su14021003

Wang, S., & Zhang, H. (2025). Enhancing SMEs Sustainable Innovation and Performance Through Digital Transformation: Insights from Strategic Technology, Organizational Dynamics, and Environmental Adaptation. *Socio-Economic Planning Sciences*, 98. https://doi.org/10.1016/j.seps.2024.102124

Yu, J., & Moon, T. (2021). Impact of Digital Strategic Orientation on Organizational Performance Through Digital Competence. *Sustainability (Switzerland)*, 13(17). https://doi.org/10.3390/su13179766

Zakaria, E., Hadiyan, H., & Lawrence, L. (2025). Impact of Digital Era Transformation on Human Resource Management. *APTISI Transactions on Management (ATM)*, 9(1), 12–19. https://doi.org/10.33050/atm.v9i1.2379