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RESEARCH ARTICLE

Digital HR, Artificial Intelligence, and Employee Engagement in the Hospitality Industry of Bagmati Province: The Mediating Role of Knowledge Management

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Abstract

Purpose: This study examines the effects of Digital Human Resource Management (Digital HR) and Artificial Intelligence (AI) on Employee Engagement (EE), with Knowledge Management (KM) as a mediator, in the hospitality sector of Bagmati Province, Nepal.

Design/methodology/approach: A quantitative, cross-sectional survey was conducted among 400 hospitality employees using convenience sampling. Data were analysed using SmartPLS 4.

Findings: Digital HR positively influenced employee engagement and knowledge management, while AI positively influenced knowledge management. Knowledge management positively influenced employee engagement and partially mediated the relationship between Digital HR and employee engagement. It fully mediated the relationship between AI and employee engagement, as the direct effect of AI on employee engagement was not significant.

Implications: Hospitality organisations should integrate Digital HR and AI with effective knowledge management practices, emphasising knowledge sharing, learning, and technology-enabled knowledge processes to strengthen employee engagement.

Originality/value: The study highlights the importance of knowledge management in translating technology-driven HR practices into greater employee engagement in Nepal's hospitality sector.

JEL Classification: D83, L83, M12, M15, O33

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Introduction

The rapid digitalisation of human resource management (HRM) has reshaped organisational practices worldwide, with Artificial Intelligence (AI) and Digital HR platforms increasingly used for recruitment, performance management, employee development, and HR analytics (Strohmeier, 2020; Volianska-Savchuk et al., 2024). In hospitality, where frontline employee performance is closely linked to organisational outcomes, the role of these technologies in fostering employee engagement is strategically important (Qayyum et al., 2025; Schaufeli et al., 2002). Employee engagement is a positive and fulfilling work-related state characterised by vigour, dedication, and absorption, and is associated with service quality, customer satisfaction, and reduced turnover (Schaufeli et al., 2002).

However, technology adoption does not automatically enhance employee engagement. Digital HR and AI can improve engagement through transparency, personalisation, and career development support (Alzeiby et al., 2025; Hizam et al., 2025; Mintawati et al., 2025), whereas AI perceived as impersonal or opaque may reduce trust and psychological safety (Naoum et al., 2026; Safshekan et al., 2026). This divergence highlights the importance of organisational mechanisms, particularly Knowledge Management (KM), which involves knowledge creation, capture, sharing, and application (Ferraris et al., 2023). Effective KM can transform knowledge generated through Digital HR and AI into learning, competence development, collaboration, and improved work experiences (Naim et al., 2024; Olan et al., 2023).

The relevance of this relationship is increasing in hospitality as AI becomes more widely adopted. A 2026 global study reported that 98% of hoteliers had used AI in their operations during the preceding six months, although the extent and strategic integration varied across properties. Similarly, a meta-analysis of 71 studies involving 23,051 hospitality employees across 37 countries found that perceived AI benefits were positively associated with AI adoption and job engagement. These findings reinforce the need to examine the mechanisms through which digital technologies influence employee outcomes.

Despite growing research on Digital HR, AI, KM, and employee engagement, these constructs have largely been examined separately or through partially connected relationships. Thus, limited evidence explains how Digital HR and AI jointly influence employee engagement and whether KM mediates these relationships, particularly in developing-country hospitality contexts. Nepal provides an important setting for addressing this gap. Bagmati Province has 62,405 salaried employees in accommodation and food-service activities (National Statistics Office, n.d.), while Digital HR and AI adoption in Nepalese hotels remains relatively nascent (Rijal, 2023; Ruel & Njoku, 2021). Existing Nepalese studies have mainly examined traditional HRM practices and workforce diversity (Malik et al., 2023; Rijal, 2023), leaving limited evidence on the Digital HR–AI–KM–Employee Engagement nexus. Moreover, contextual factors such as collectivist organisational culture and informal knowledge-sharing practices may influence technology-enabled HRM outcomes (Sharma et al., 2025).

The study further addresses a theoretical integration gap by drawing on Self-Determination Theory (SDT), the Job Demands–Resources (JD-R) Model, and Social Exchange Theory (SET). SDT explains how resources and knowledge may satisfy employees' psychological needs and support engagement (Deci & Ryan, 2000); the JD-R Model positions Digital HR and AI as job resources that can reduce demands and enhance motivation (Bakker & Demerouti, 2017); and SET suggests that supportive organisational practices may encourage reciprocal positive attitudes and behaviours (Blau, 2017; Cropanzano & Mitchell, 2005).

Accordingly, this study addresses three gaps. First, limited research has simultaneously examined Digital HR and AI as distinct predictors of employee engagement with KM as a mediator. Second, the mediating role of KM in transmitting the effects of both technologies on engagement remains under-tested. Third, empirical evidence from developing-country hospitality contexts, particularly Nepal, is scarce. Therefore, this study integrates Digital HR, AI, KM, and Employee Engagement to examine whether KM serves as a mechanism through which digital technologies contribute to employee engagement in Nepal's hospitality sector.

Literature Review

Digital HR and Employee Engagement

Digital human resource management (Digital HR) refers to the application of digital technologies to automate, optimise, and strategically transform traditional HR functions. These technologies include e-recruitment, digital onboarding, cloud-based performance management, employee self-service portals, and HR analytics (Strohmeier, 2020; Volianska-Savchuk et al., 2024). The growing adoption of Digital HR has transformed the way organisations interact with employees by improving the accessibility, transparency, responsiveness, and personalisation of HR services. Recent studies suggest that Digital HR practices can positively influence employee engagement by facilitating efficient communication, timely feedback, career development, and employee participation (Hizam et al., 2025; Mintawati et al., 2025; Yang & Zhang, 2025). For example, digital performance management systems can help align individual and organisational goals, while career development platforms can strengthen employee motivation and commitment. Similarly, employee self-service technologies reduce administrative burdens and allow employees to devote greater cognitive resources to meaningful work activities (Stachová et al., 2024).

The positive relationship between Digital HR and employee engagement can be explained through SET. According to SET, when employees perceive that their organisation invests resources to improve their work experience and support their professional development, they are likely to reciprocate through positive attitudes and behaviours, including higher engagement (Cropanzano & Mitchell, 2005). Similarly, the JD-R model suggests that organisational resources can reduce job demands and stimulate motivational processes that enhance employee engagement (Bakker & Demerouti, 2017). Digital HR technologies can therefore function as important job resources by improving access to information, simplifying HR processes, and supporting employees in performing their work effectively.

However, the availability of digital technologies alone may not automatically lead to greater employee engagement. The information and resources generated through digital HR systems must be effectively captured, shared, and applied within the organisation. Employees may derive greater benefits from Digital HR when organisations possess effective knowledge management mechanisms that enable them to access and utilise relevant information. Therefore, Knowledge Management may represent an important mechanism through which Digital HR practices are translated into meaningful employee experiences and engagement outcomes

Artificial Intelligence in HRM and Employee Engagement

AI in human resource management refers to the application of technologies such as machine learning, natural language processing, robotic process automation, and predictive analytics in HR activities, including recruitment, employee selection, performance evaluation, personalised learning, and employee well-being management (Chowdhury et al., 2022; Kulikowski, 2024). The increasing integration of AI into HRM has created new opportunities for organisations to improve efficiency, personalise employee experiences, and make data-driven decisions. AI-powered applications such as virtual assistants, intelligent coaching systems, predictive career guidance, and automated learning platforms have been associated with improved employee experiences and engagement, particularly when employees perceive these technologies as supportive rather than controlling (Alzeiby et al., 2025; Asim & Ding, 2025; Diatmono, 2026).

Recent scholarship indicates that algorithmic systems are increasingly used across a wide range of HR functions, including recruitment, applicant screening, performance assessment, workforce monitoring, compensation decisions, and predictive workforce analytics. Such systems can process large volumes of employee data, identify complex patterns, and support decision-making at a scale beyond conventional HR information systems (Manoharan et al., 2026).

However, the autonomous and adaptive characteristics of AI systems also create challenges related to transparency, accountability, and employee perceptions. The relationship between AI adoption and employee engagement is therefore complex. Positive employee outcomes depend significantly on employee trust, perceptions of fairness, and the transparency of algorithmic processes (Naoum et al., 2026). In service-oriented industries, where interpersonal relationships and human interaction are central to work, AI technologies perceived as impersonal, opaque, or unfair may generate resistance rather than engagement (Safshekan et al., 2026). Research on algorithmic HRM further suggests that perceived fairness in AI-enabled HR practices can influence employee trust, commitment, engagement, and cooperative behaviours. When employees perceive algorithmic systems as biased or difficult to understand, trust in organisational processes may decline, potentially weakening the psychological relationship between employees and their organisation (Manoharan et al., 2026).

The effective implementation of AI in HRM therefore requires more than technological capability. Appropriate mechanisms for transparency, accountability, monitoring, and employee participation are necessary to ensure that AI systems are perceived as supportive and trustworthy. In particular, human oversight remains important in high-stakes HR decisions. AI-generated recommendations may support managerial decision-making, but they should not necessarily replace human judgment. A human-in-the-loop approach can help organisations ensure that algorithmic decisions remain aligned with organisational values, fairness, and employee welfare (Manoharan et al., 2026). Thus, the engagement effects of AI are not inherent in the technology itself but depend on how AI-generated information is interpreted, communicated, and integrated into organisational processes. This suggests that Knowledge Management may play an important role in converting AI-generated information into meaningful knowledge and positive employee experiences.

Knowledge Management and Employee Engagement

Knowledge Management (KM) refers to the systematic process of creating, acquiring, capturing, sharing, and applying knowledge to improve organisational performance and facilitate organisational learning (Ferraris et al., 2023). In contemporary organisations, KM increasingly involves the integration of digital repositories, learning management systems, AI-powered recommendation platforms, and collaborative knowledge-sharing practices such as communities of practice and peer mentoring (Olan et al., 2023). Effective KM enables employees to access relevant information, learn from organisational experiences, share expertise, and apply knowledge to solve work-related problems.

Previous research has demonstrated that effective KM practices can positively influence employee engagement. Knowledge sharing, acquisition, and application can enhance employee competence, reduce task uncertainty, and create collaborative work environments, thereby strengthening employees' psychological connection with their work and organisation (Ferraris et al., 2023; Naim et al., 2024). When employees have access to relevant organisational knowledge, they are better able to perform their roles effectively and develop confidence in their professional capabilities.

The increasing use of AI and digital technologies further highlights the importance of KM. Although AI systems can generate substantial amounts of information and insights, the value of these outputs depends on whether organisations can effectively interpret, disseminate, and apply them. Research on algorithmic HRM emphasises the importance of organisational capabilities, including AI literacy, technical expertise, stakeholder engagement, monitoring, and feedback mechanisms, in enabling organisations to respond effectively to AI-generated outcomes (Manoharan et al., 2026). This suggests that technological information alone does not automatically create organisational value; rather, value emerges when information is transformed into accessible and actionable knowledge.

In the hospitality industry, the importance of KM is particularly significant because employees frequently require access to real-time information regarding guest preferences, service standards, operational procedures, and service recovery strategies. Access to organised and relevant knowledge can improve employees' confidence and their ability to respond effectively to service challenges, thereby strengthening their emotional investment in their work (Hizam et al., 2025). From the perspective of Self-Determination Theory, KM can fulfil employees' psychological needs for competence through access to relevant knowledge and relatedness through collaborative knowledge-sharing practices. The fulfilment of these psychological needs can subsequently enhance intrinsic motivation and employee engagement (Deci & Ryan, 2000; Gagné & Deci, 2005).

The Mediating Role of Knowledge Management

The mediating role of Knowledge Management in the relationship between Digital HR, AI, and employee engagement can be explained through the JD-R model. According to the JD-R framework, organisational resources contribute to employee motivation and engagement by supporting employees in achieving work goals, reducing job demands, and promoting learning and development (Bakker & Demerouti, 2017). Digital HR and AI can provide employees with technological and informational resources by improving access to information, facilitating communication, supporting decision-making, and generating knowledge-related insights. However, the availability of these technological resources may not directly translate into employee engagement unless employees are able to access, understand, share, and apply the information effectively.

Knowledge Management can serve as a mechanism that converts technological resources into meaningful employee-level resources. Through knowledge acquisition, sharing, and application, KM enables employees to utilise information generated through Digital HR and AI systems in ways that improve competence, collaboration, and work effectiveness (Malik et al., 2022). In this sense, Digital HR and AI may enhance organisational knowledge processes, which subsequently contribute to greater employee engagement.

Recent research on algorithmic HRM supports the importance of complementary organisational capabilities in determining the outcomes of technological adoption. Manoharan et al. (2026) argue that effective AI governance requires organisational learning, stakeholder engagement, monitoring, feedback, and the continuous adaptation of organisational mechanisms. These processes are closely connected to KM because they involve the creation, sharing, interpretation, and application of knowledge across different organisational actors. Accordingly, the effectiveness of AI and Digital HR may depend not only on technological sophistication but also on an organisation's ability to manage the knowledge generated through these technologies.

Empirical studies provide further support for this mechanism. Olan et al. (2023) found that AI can strengthen knowledge-sharing processes and organisational performance by supporting more effective knowledge management. Similarly, Úbeda-García et al. (2025) identified a close strategic relationship between AI and KM, particularly in relation to the creation, dissemination, and utilisation of organisational knowledge. Nguyen (2025) further demonstrated that AI can enhance employee engagement in service organisations through knowledge acquisition and sharing processes, providing evidence for a knowledge-based mechanism linking technological adoption and employee outcomes. Likewise, Mintawati et al. (2025) found that Digital HR practices can enhance employee engagement by facilitating knowledge innovation among employees.

Furthermore, research suggests that employees are more likely to respond positively to AI-enabled HR systems when these technologies are accompanied by transparency, accountability, human oversight, and opportunities for employee participation (Manoharan et al., 2026). These conditions require effective knowledge flows among technology specialists, HR professionals, managers, and employees. Knowledge Management can therefore facilitate the interpretation and dissemination of technological information, reduce uncertainty associated with new technologies, and enable employees to understand and effectively utilise AI- and digitally generated resources.

Thus, the existing literature suggests that Digital HR and AI may not enhance employee engagement solely through their technological capabilities. Their positive effects are likely to depend on how effectively organisations manage the information and knowledge generated through these technologies. Knowledge Management therefore represents a plausible mediating mechanism through which Digital HR and AI are translated into employee-level resources, enhanced competence, improved collaboration, and ultimately greater employee engagement. However, empirical research examining the joint mediating role of Knowledge Management in the relationships between Digital HR, AI, and employee engagement remains limited, particularly in developing-country hospitality contexts. This gap provides the theoretical and empirical foundation for the present study.

Conceptual Framework

Based on the literature and theoretical foundations, this study proposes a conceptual framework linking Digital HR, Artificial Intelligence (AI), Knowledge Management (KM), and Employee Engagement (EE). Digital HR and AI are the independent variables, KM is the mediating variable, and EE is the dependent variable. Drawing on the JD-R Model, Digital HR and AI provide technological resources that can enhance employee engagement (Bakker & Demerouti, 2017). They can also facilitate knowledge acquisition, sharing, and application, enabling KM to act as a mechanism through which technology contributes to engagement (Olan et al., 2023; Mintawati et al., 2025). Effective KM further supports employee competence, collaboration, and engagement (Ferraris et al., 2023; Naim et al., 2024). Thus, the framework proposes both direct effects of Digital HR and AI on EE and indirect effects through KM.

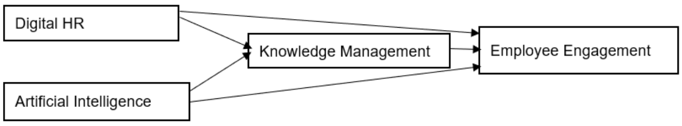

Figure 1: Conceptual Framework

Note. Adapted from Qayyum et al (2025); Stachová et al (2024)

Building on the foregoing theoretical perspectives and empirical evidence, this study develops and empirically tests the following hypotheses

H1: Digital HR has a significant positive effect on Employee Engagement.

H2: Artificial Intelligence has a significant positive effect on Employee Engagement.

H3: Knowledge Management has a significant positive effect on Employee Engagement.

H4: Digital HR has a significant positive effect on Knowledge Management.

H5: Artificial Intelligence has a significant positive effect on Knowledge Management.

H6: Knowledge Management significantly mediates the relationship between Digital HR and Employee Engagement.

H7: Knowledge Management significantly mediates the relationship between Artificial Intelligence and Employee Engagement.

Research Methods

Research Design and Sample

This study adopted a post-positivist research approach to empirically investigate the hypothesised relationships among the study variables. Seven hypotheses were formulated based on SDT, the JD-R model, and SET theory (Creswell & Creswell, 2018; Sekaran & Bougie, 2016). The target population comprised salaried employees working in hotels, resorts, lodges, and other accommodation and food-service establishments across Bagmati Province, Nepal, with a total population of 62,405 employees (National Statistics Office, n.d.). Using the Yamane (1967) formula at a 5% margin of error, the minimum required sample size was determined to be 397 respondents. Given the absence of a comprehensive sampling frame of eligible employees, convenience sampling was employed to facilitate access to respondents across the target establishments.

Data were collected from January to February 2026 using a structured questionnaire administered through online (n = 300) and printed (n = 100) modes. Respondents were approached through professional networks, direct contact with hospitality establishments, and hotel employees. The combined approach facilitated access to employees across diverse hospitality settings. The final sample comprised 400 valid responses, exceeding the minimum requirement for PLS-SEM analysis (Hair et al., 2019). Respondents represented 1-star (15.0%), 2-star (22.3%), 3-star (15.5%), 4-star (15.3%), lodge (14.0%), and resort (17.0%) establishments. These categories were included to provide coverage across different hospitality settings, with the observed distribution reflecting accessibility under convenience sampling. Ethical principles were maintained through voluntary participation, informed consent, anonymity, confidentiality, and academic use of the data.

Measures

All constructs were measured using validated Likert-scale instruments anchored from 1 (Strongly Disagree) to 5 (Strongly Agree). Digital HR was operationalised using seven items adapted from Strohmeier (2020), capturing digitalisation of HR processes including e-recruitment, performance management, data-driven decision-making, and employee self-service. AI in HR was measured using six items adapted from Dima et al. (2024), assessing AI applications in candidate screening, performance evaluation, knowledge sharing, and HR decision support (one item was dropped during measurement model refinement for insufficient loading). KM was measured with six items adapted from Naim et al. (2024), assessing knowledge sharing, knowledge acquisition, knowledge awareness, and knowledge application (one item was dropped during refinement). Employee Engagement was operationalised using seven items from the Utrecht Work Engagement Scale (UWES; Schaufeli et al., 2002), capturing vigour, dedication, and absorption.

Data Analysis

Data were analysed using PLS-SEM via SmartPLS 4 and IBM SPSS Statistics 26, following the two-stage approach recommended by Hair et al. (2019). PLS-SEM was selected because the study examined multiple latent constructs and the mediating role of Knowledge Management within an integrated model, with an emphasis on predicting employee engagement. In Stage 1, the measurement model was assessed for internal consistency reliability (Cronbach's α and Composite Reliability ≥ .70), convergent validity (AVE ≥ .50), and discriminant validity using the HTMT criterion (< .85). In Stage 2, the structural model was evaluated using path coefficients, mediating effects, R^2, f^2, VIF (< 5.0), and SRMR (< .08). Mediation was tested using 5,000 bootstrap resamples with bias-corrected 95% confidence intervals. Statistical significance was determined at $t > 1.96$ and $p < 0.05$.

Results

Socio-Demographic Profile

Table 1 summarises the demographic characteristics of the 400 respondents. The sample was relatively diverse in terms of gender, age, education, work experience, job position, and establishment type. The largest age group was 30–35 years (24%), while Master's degree holders constituted the largest educational group (34%). Respondents with 1–3 years of work experience represented the largest experience category (31.5%), and supervisors accounted for the largest proportion by job position (36.5%).

Table 1: *Demographic Profile of the Respondents*

Demographics	Characteristics	Frequency	Percentage (%)
Gender	Female	184	46
	Male	156	39
	Prefer not to say	60	15
Age	25-30	84	21
	30-35	96	24
	35-40	59	15
	40-45	60	15
	Above 45	41	10
	Below 25	59	15
Education	Bachelor Degree	96	24
	M.Phil.	56	14
	Master Degree	136	34
	PhD	32	8
	Post Graduate	79	20
Work Experience	1-3 years	126	31.5
	4-6 years	99	24.8
	7-10 years	54	13.5
	Above 10 years	35	8.8
	Less than 1 year	85	21.3
Job Position	Entry Level	114	28.5
	Senior Level	139	34.8
	Supervisor Level	146	36.5
Star Rating	1 Star	61	15
	2 Star	89	22.3
	3 Star	62	15.5
	4 Star	61	15.3
	Lodge	55	14
	Resort	68	17

Note. Calculations based on the authors' survey (2026)

Descriptive Analysis of Constructs

Descriptive statistics were calculated to assess respondents' perceptions of Digital HR, AI, KM, and Employee Engagement. As presented in Table 2, all four constructs recorded mean scores above the midpoint (3.00), indicating generally positive perceptions. Among the technology- and knowledge-related constructs, AI had the highest mean (M = 3.937, SD = .681), followed by KM (M = 3.921, SD = .703) and Digital HR (M = 3.902, SD = .796). Employee Engagement recorded the highest overall mean (M = 4.579, SD = .602), indicating a high level of employee engagement among the respondents. At the item level, EE4 ("I am fully focused on my work") recorded the highest mean (M = 4.632, SD = .581), whereas D7 ("Digital HR contributes to better employee engagement in my organisation") recorded the lowest mean (M = 3.832, SD = .803). Overall, the findings indicate favourable perceptions of digital HR practices, AI, knowledge management, and employee engagement.

Table 2. Descriptive Analysis of Constructs

Construct	Item	Mean	SD
Digital HR	D1	3.884	.78
	D2	3.916	.78
	D3	3.926	.80
	D4	3.863	.85
	D5	3.958	.81
	D6	3.937	.75
	D7	3.832	.80
	Overall	3.902	.80
Artificial Intelligence	AI1	3.937	.66
	AI2	3.895	.62
	AI3	3.958	.70
	AI4	3.947	.64
	AI5	3.926	.74
	AI6	3.958	.72
	Overall	3.937	.68
Knowledge Management	KM1	3.895	.72
	KM2	3.947	.70
	KM3	3.979	.65
	KM4	3.832	.74
	KM5	3.895	.72
	KM7	3.979	.70
	Overall	3.921	.70
Employee Engagement	EE1	4.621	.55
	EE2	4.579	.59
	EE3	4.495	.71
	EE4	4.632	.58
	EE5	4.547	.59
	EE6	4.6	.57
	EE7	4.579	.63
	Overall	4.579	.60

Note. Calculations based on authors' survey data, 2025

Measurement Model Assessment

Construct Reliability and Validity: Table 3 presents the construct reliability and convergent validity results. All constructs demonstrate satisfactory internal consistency, with Cronbach's α and Composite Reliability values exceeding the recommended threshold of .70. The AVE values are also above .50, supporting convergent validity.

Table 3: Construct Reliability and Validity

Construct	Cronbach's α	CR (rho_a)	CR (rho_c)	AVE
Artificial Intelligence (AI)	.85	.856	.889	.572
Digital HR (D)	.897	.90	.919	.617
Employee Engagement (EE)	.904	.905	.924	.634
Knowledge Management (KM)	.842	.843	.884	.559

Note. CR = Composite Reliability; AVE = Average Variance Extracted. All values meet or exceed Hair et al. (2019) thresholds (α, CR ≥ .70; AVE ≥ .50).

Discriminant Validity: Table 4 presents the HTMT results. All HTMT values range from .634 to .733 and remain below the conservative threshold of .85, confirming adequate discriminant validity among the constructs.

Table 4*:* HTMT Ratio

	Heterotrait-monotrait ratio (HTMT)
D <-> AI	.684
EE <-> AI	.634
EE <-> D	.674
KM <-> AI	.733
KM <-> D	.686
KM <-> EE	.731

Note. D = Digital HR; AI = Artificial Intelligence; EE = Employee Engagement; KM = Knowledge Management.

Table 5 presents the Fornell–Larcker criterion. The square root of AVE for each construct is higher than its correlations with the other constructs, supporting discriminant validity.

Table 5: *Fornell Larcker's Test*

	AI	D	EE	KM
AI	.756			
D	.605	.786		
EE	.567	.611	.796	
KM	.63	.606	.638	.748

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

Structural Model Results

Model fit was acceptable: SRMR = .069 (below the .08 threshold; Hu & Bentler, 1999), though NFI = 0.766, which, while below the conventional .90 threshold, is less emphasised in PLS-SEM (Hair et al., 2019). Variance Inflation Factor (VIF) values ranged from 1.466 to 2.501, well below the threshold of 5.0, ruling out multicollinearity concerns. The structural model explained 50.1% of the variance in Employee Engagement (R^2 = .501) and 47.7%

of variance in Knowledge Management (R^2 = .477), indicating moderate-to-substantial predictive power.

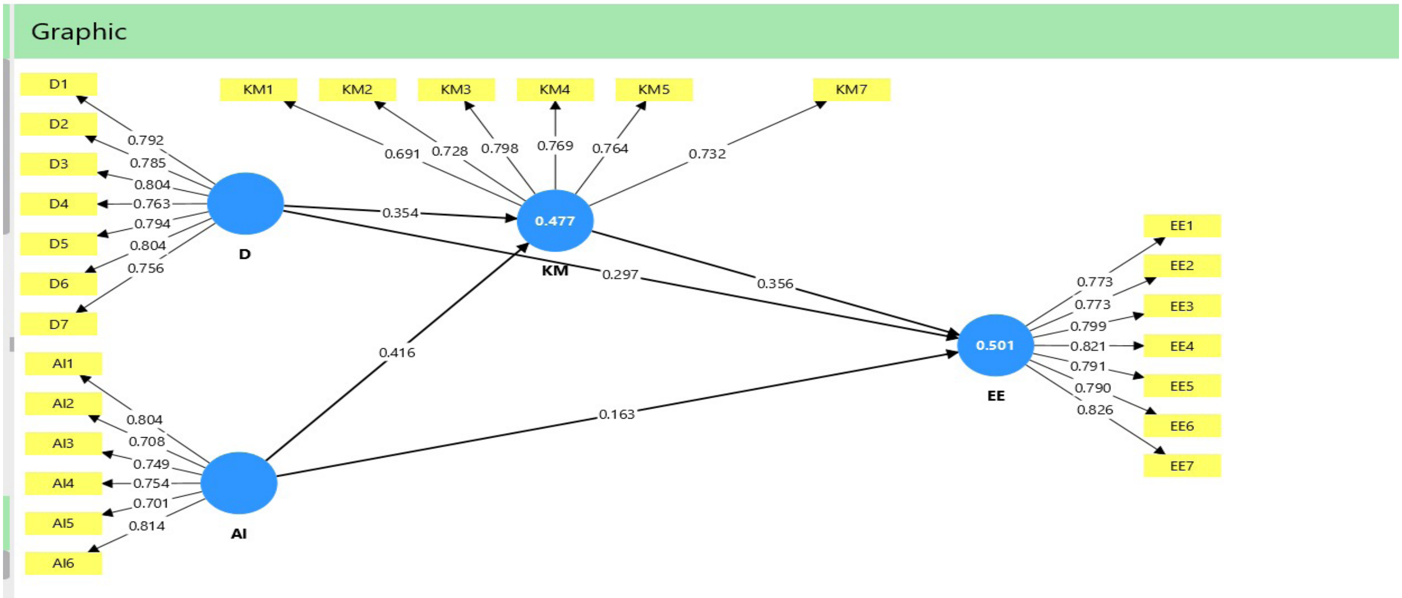

Figure 2: Path Diagram

Table 6: *Structural Model Path Coefficients (Direct Effects)*

Hypothesis	Path	β	t-statistic	p-value	95% CI	Decision
H1	Digital HR → EE	.297	3.181	.001	[.110, .479]	Supported
H2	AI → EE	.163	1.718	.086	[-.025, .348]	Not Supported
H3	KM → EE	.356	3.676	<.001	[.171, .549]	Supported
H4	Digital HR → KM	.354	3.595	<.001	[.155,.532]	Supported
H5	AI → KM	.416	4.547	<.001	[.244, .603]	Supported

Note. β = standardised path coefficient; CI = confidence interval based on 5,000 bootstrap resamples; EE = Employee Engagement; KM = Knowledge Management.

Table 6 presents the path coefficient results. Digital HR had significant and positive effects on both Employee Engagement (*β = .297, t = 3.181, p = .001*) and KM (*β = .354, t = 3.595, p < .001*), supporting H1 and H4. AI had a significant and positive effect on KM (*β = .416, t = 4.547, p < .001*), supporting H5; however, its direct effect on Employee Engagement was not statistically significant (*β = .163, t = 1.718, p = .086*), leading to the rejection of H2. KM, in turn, had a significant and positive effect on Employee Engagement (*β = .356, t = 3.676, p < .001*), supporting H3.

Mediation Analysis

Table 7 reports the specific indirect effects. Knowledge Management (KM) fully mediated the relationship between Artificial Intelligence (AI) and Employee Engagement (EE), with a significant indirect effect (*β = .148, t = 2.853, p = .004*), supporting H7. Since the direct AI → EE path was non-significant while the indirect effect through KM was significant, full mediation was established (Baron & Kenny, 1986; Preacher & Hayes, 2008). KM also partially mediated the relationship between Digital HR and Employee Engagement, with a significant indirect effect (*β = .126, t = 2.487, p = .013),* supporting H6. In this case, the direct Digital HR → EE path remained significant alongside the significant indirect effect, confirming partial mediation. Furthermore, the total effect of AI on Employee Engagement was significant (*β = .311, t = 3.292, p = .001*), further highlighting the important role of KM as an underlying mechanism through which AI contributes to employee engagement.

Table 7: Mediation Analysis: Specific Indirect Effects via Knowledge Management

Hypothesis	Indirect Path	β	t-statistic	p-value	95% CI	Mediation Type
H6	Digital HR → KM → EE	0.126	2.487	0.013	[0.039, 0.238]	Partial Mediation
H7	AI → KM → EE	0.148	2.853	0.004	[0.061, 0.265]	Full Mediation

Note. Indirect effects computed using 5,000 bootstrap resamples with bias-corrected 95% confidence intervals. KM =

Knowledge Management; EE = Employee Engagement.

Effect Sizes

Effect size analysis (f^2) revealed that AI exerted a large effect on KM (f^2 = .425), while KM exerted a large effect on Employee Engagement (f^2 = .379), together constituting the dominant pathway in the model. Digital HR demonstrated a small-to-medium effect on KM (f^2 = .091) and a small effect on Employee Engagement (f^2 = .059), while AI's direct effect on Employee Engagement was also small (f^2 = .136). Thus, these effect sizes indicate that the AI–KM–Employee Engagement pathway represents the primary mechanism underlying engagement in the model.

Discussion

This study examined the relationships among Digital HR, AI, KM, and EE in the Nepalese hospitality sector. The findings provide evidence that both Digital HR and AI contribute to organisational knowledge processes, although their effects on employee engagement differ. Digital HR has both direct and indirect effects on employee engagement through KM, whereas AI influences employee engagement indirectly through KM. The findings of each hypothesis are discussed chronologically below.

Digital HR has a significant positive effect on Employee Engagement

The findings support H1, indicating that Digital HR has a significant positive effect on EE. This finding is consistent with previous studies that have reported a positive association between digital HR practices and EE (Mintawati et al., 2025; Hizam et al., 2025; Stachová et al., 2024; Yang & Zhang, 2025). These studies suggest that digital HR systems improve employees' access to HR services, performance information, learning opportunities, communication, and feedback, which can encourage employees to become more involved and psychologically connected with their work.

The positive relationship can be explained through SET. Digital HR practices such as e-performance dashboards, digital learning platforms, and employee self-service systems may be perceived by employees as organisational investments in their development and wellbeing. In response to such favourable treatment, employees may reciprocate through greater effort, commitment, and engagement, consistent with the reciprocity principle of SET (Cropanzano & Mitchell, 2005; Blau, 2017). The finding is also consistent with the JD-R Model, according to which digital HR systems can function as job resources by reducing administrative burdens, improving access to performance feedback, and facilitating learning and career development (Bakker & Demerouti, 2017).

However, the strength of this relationship may differ from findings in technologically mature economies because the level of HR digitalisation varies across contexts. In Nepalese hospitality organisations, where HR activities may still involve manual and informal processes, the introduction of digital HR can represent a relatively significant improvement in employees' access to organisational services and information. Therefore, the positive relationship found in this study may reflect the greater perceived value of digital HR in a developing technological environment. Thus, the finding indicates that digitalisation of HR functions can enhance not only administrative efficiency but also employees' psychological involvement in their work.

Digital HR has a significant positive effect on Knowledge Management

The findings support H2, demonstrating that Digital HR has a significant positive effect on Knowledge Management. This finding is consistent with previous research showing that digital HR systems can facilitate knowledge creation, storage, sharing, and application within organisations (Volianska-Savchuk et al., 2024; Yang & Zhang, 2025). Digital HR platforms create structured channels for storing employee and organisational information and provide employees with easier access to learning materials, performance information, and organisational knowledge.

The finding can be explained through SDT. Digital HR platforms can enhance employees' sense of competence by providing timely feedback, training opportunities, and access to information required for performing their jobs effectively (Deci & Ryan, 2000). When employees have greater access to relevant knowledge and learning resources, they may become more capable of acquiring, applying, and sharing knowledge. Digital systems can also facilitate communication among employees, thereby supporting the dissemination of knowledge across organisational units.

The relationship may be particularly important in the hospitality sector because service delivery is highly dependent on timely and accurate knowledge. Employees need to understand customer preferences, service standards, organisational procedures, and methods of handling unexpected service situations. Digital HR systems can make such knowledge more accessible and systematically organised. Thus, the finding suggests that Digital HR contributes to KM not simply by digitising HR activities but by creating an organisational environment that supports continuous learning and knowledge exchange.

AI has a significant positive effect on Employee Engagement

The findings do not support H3, as AI does not have a significant direct effect on EE. This finding contradicts studies that have identified a positive direct relationship between AI and employee engagement (Asim & Ding, 2025; Alzeiby et al., 2025; Diatmono, 2026). The contradictory findings indicate that the effect of AI on employee engagement may be dependent on organisational and contextual conditions rather than being universally positive.

One possible reason for the non-significant relationship is the relatively early stage of AI adoption in Nepalese hospitality organisations. In technologically advanced organisational environments, employees may interact extensively with AI through recruitment, scheduling, performance management, learning, decision support, and customer service systems. Such extensive interaction may allow employees to directly experience the benefits of AI in their daily work. In contrast, employees in Nepalese hospitality organisations may have more limited exposure to AI, meaning that AI has not yet become sufficiently integrated into their everyday work to produce a measurable direct effect on engagement.

The finding can also be interpreted through SDT. AI may enhance engagement when employees perceive it as increasing their autonomy, competence, and ability to perform meaningful work (Deci & Ryan, 2000). However, if AI is primarily viewed as a technological tool rather than as a resource that directly supports employees, these psychological needs may not be sufficiently activated. From an SET perspective, employees may also be less likely to reciprocate AI implementation if they perceive it as primarily benefiting organisational efficiency rather than employee wellbeing. Moreover, AI applications associated with automated monitoring, evaluation, or impersonal decision-making may generate uncertainty or concerns about reduced human interaction, potentially limiting their positive influence on engagement (Naoum et al., 2026).

Therefore, the non-significant finding should not be interpreted as evidence that AI has no relevance to employee engagement. Rather, it suggests that the effect of AI may occur through an intervening organisational mechanism, particularly Knowledge Management.

AI has a significant positive effect on Knowledge Management

The findings support H4, showing that AI has a significant positive effect on Knowledge Management. This result is consistent with previous studies demonstrating that AI can enhance organisational knowledge processes through data analytics, intelligent recommendation systems, automated information processing, and digital learning technologies (Olan et al., 2023; Bernik & Šprajc, 2025).

Importantly, AI demonstrated the largest effect size on KM in the model ($f^2 = .425$). This indicates that AI plays a particularly important role in strengthening knowledge-related activities within the organisations studied. AI can process large volumes of information, identify patterns, provide recommendations, and make relevant information more accessible to employees. In hospitality organisations, these capabilities can support the management of information relating to customers, service quality, employee performance, training, and operational procedures.

The strong AI–KM relationship also helps explain the non-significant direct relationship between AI and EE found under H3. AI may initially generate organisational rather than psychological benefits. That is, employees may not immediately become more engaged simply because AI is introduced, but they may benefit from improved access to knowledge and information generated through AI-supported systems. These knowledge resources can subsequently improve employees' competence and reduce uncertainty in performing their tasks.

The finding can therefore be linked with SDT because AI-supported knowledge systems can provide employees with resources that improve their competence and learning opportunities. The result also highlights the importance of organisational context. In an emerging AI environment such as Nepal, organisations may initially derive greater value from AI in information processing and knowledge management than from direct changes in employee attitudes. Thus, AI appears to function primarily as an enabler of organisational knowledge rather than as an immediate driver of employee engagement.

Knowledge Management has a significant positive effect on Employee Engagement

The findings support H5, demonstrating that Knowledge Management has a significant positive effect on Employee Engagement. This finding is consistent with previous studies that have identified KM as an important factor contributing to employee engagement (Ferraris et al., 2023; Naim et al., 2024). Effective KM provides employees with access to relevant information, opportunities for learning, and mechanisms for collaboration, which can improve their ability and willingness to engage in their work.

The finding is strongly supported by SDT. Effective KM can satisfy employees' need for competence by providing the knowledge and resources required to perform their tasks successfully. It can also support relatedness by facilitating interaction, collaboration, and knowledge sharing among employees (Deci & Ryan, 2000; Gagné & Deci, 2005). When employees feel competent and connected with colleagues, they are more likely to experience greater enthusiasm and involvement in their work.

The JD-R Model provides another explanation. Knowledge availability can act as a job resource by reducing task uncertainty and helping employees cope with job demands (Bakker & Demerouti, 2017). This is particularly relevant to hospitality organisations, where employees frequently face unpredictable customer needs, time pressure, and service-related challenges. Ready access to organisational knowledge can enable employees to respond to such demands more confidently and effectively, thereby supporting vigour, dedication, and absorption.

The finding therefore demonstrates that KM is not only an organisational mechanism for managing information but also an important employee resource. In the hospitality context, where effective service delivery depends heavily on timely knowledge exchange, organisations with stronger KM practices may create working environments in which employees are better equipped, more confident, and more engaged.

Knowledge Management mediates the relationship between Digital HR and Employee Engagement

The findings support H6, indicating that Knowledge Management significantly mediates the relationship between Digital HR and Employee Engagement. This finding extends the results of H1 and H2 by demonstrating that the positive effect of Digital HR on employee engagement occurs through two pathways: a direct pathway and an indirect pathway through KM.

The finding is consistent with the broader literature suggesting that digital HR technologies can strengthen organisational knowledge processes, which subsequently improve employee outcomes (Volianska-Savchuk et al., 2024; Yang & Zhang, 2025). However, the present finding provides additional insight by demonstrating that the engagement benefits of Digital HR are not limited to improved HR service delivery. Digital HR also creates a knowledge-rich environment that contributes to employee engagement.

The partial mediation is theoretically consistent with SET, JD-R, and SDT. Under SET, employees may respond positively to digital HR because it signals organisational support and investment. At the same time, the knowledge resources created through digital systems provide employees with tangible benefits that can further encourage engagement. Under the JD-R Model, digital HR acts as a job resource that facilitates access to knowledge, feedback, and learning opportunities, while KM transforms these resources into practical support for employees (Bakker & Demerouti, 2017). From the SDT perspective, access to learning and knowledge can strengthen competence, while digital knowledge-sharing systems can support relatedness.

The partial rather than full mediation is also important. It indicates that KM explains part, but not all, of the Digital HR–Employee Engagement relationship. Digital HR can therefore influence engagement directly through improved HR services, communication, feedback, and perceptions of organisational support, while KM represents an additional pathway through which digital HR generates engagement. This finding suggests that organisations should not merely digitise HR transactions; they should design digital HR systems in ways that actively facilitate learning, knowledge sharing, and collaboration.

Knowledge Management mediates the relationship between AI and Employee Engagement

The findings support H7, demonstrating that Knowledge Management fully mediates the relationship between AI and Employee Engagement. This is the most theoretically significant finding of the study because AI did not have a significant direct effect on employee engagement, but it had a strong positive effect on KM, which subsequently influenced employee engagement.

The finding differs from studies reporting a direct positive relationship between AI and employee engagement (Asim & Ding, 2025; Alzeiby et al., 2025; Diatmono, 2026). The difference may be explained by variations in technological maturity and the extent to which AI is integrated into employees' daily work. In technologically advanced settings, AI may directly influence employees by increasing productivity, autonomy, and access to personalised resources. In Nepalese hospitality organisations, however, AI adoption may still be sufficiently limited that employees do not directly experience these psychological benefits. Instead, the primary organisational benefit of AI appears to occur through improved knowledge processes.

The strong effect of AI on KM provides support for this interpretation. AI can facilitate knowledge capture, processing, retrieval, and dissemination through analytics, intelligent recommendations, automated information processing, and personalised learning systems (Olan et al., 2023; Bernik & Šprajc, 2025). The resulting improvement in knowledge availability can enhance employees' competence, reduce task uncertainty, and facilitate collaboration, which can ultimately strengthen engagement (Naim et al., 2024).

The full mediation can be explained through SDT and the JD-R Model. AI itself may not directly satisfy employees' psychological needs; however, AI-generated knowledge resources can enhance competence by helping employees acquire and apply relevant knowledge. Similarly, AI-supported KM can function as a job resource that helps employees manage work demands and perform their roles more effectively. Consequently, the engagement effect emerges after AI capabilities are translated into usable organisational knowledge.

From a contextual perspective, the finding suggests that AI should not automatically be considered a direct employee-engagement tool, particularly in developing economies where AI adoption is still emerging. Instead, organisations may need to focus on converting AI capabilities into accessible knowledge, learning, and collaboration resources. The finding therefore extends existing literature by positioning KM as the key mechanism through which AI generates employee-level outcomes in the Nepalese hospitality sector.

Taken together, the findings reveal a differentiated mechanism through which digital technologies influence employee engagement. Digital HR has a significant direct effect on Employee Engagement and also contributes to engagement indirectly through Knowledge Management. AI, in contrast, does not have a significant direct effect on Employee Engagement but has a strong positive effect on Knowledge Management, which subsequently leads to higher engagement through full mediation.

These findings demonstrate that the influence of digital technologies on employees is not uniform. Digital HR, being more directly related to employees' HR experiences, can immediately generate perceptions of organisational support and provide job resources that enhance engagement. AI, however, appears to operate primarily at the organisational knowledge level in the Nepalese hospitality context. Its employee-level benefits become evident when AI-generated capabilities are transformed into useful knowledge resources.

Thus, the results support the complementary role of SET, SDT, and the JD-R Model. SET explains how employee-oriented digital HR investments can generate reciprocal engagement; SDT explains how access to knowledge, learning, competence, and collaboration can strengthen employee motivation; and the JD-R Model explains how Digital HR and KM provide resources that help employees manage job demands. The findings consequently suggest that the value of emerging technologies lies not only in their technological capabilities but also in how organisations translate those capabilities into meaningful resources and experiences for employees.

Conclusion and Implications

This study examined Digital HR, AI, KM, and EE among hotel employees in Bagmati Province, Nepal. The findings indicate that Digital HR, AI, KM, and EE are significantly interconnected, with Digital HR positively influencing both KM and EE, while AI significantly enhances KM but has no direct effect on EE. KM significantly improves EE and partially mediates the Digital HR–EE relationship while fully mediating the AI–EE relationship.

The findings suggest that Knowledge Management is the critical mechanism through which digital technologies generate employee engagement, particularly for AI. Thus, technology adoption alone is insufficient to improve engagement; its value depends on how effectively hotels transform digital capabilities into accessible knowledge, learning, collaboration, and employee support. This is particularly important in hospitality, where timely knowledge and effective information sharing directly support service quality and employees' ability to respond to customer and operational demands.

The study therefore implies that Nepalese hotels should integrate Digital HR and AI with effective KM practices rather than treating technological adoption as an end in itself. Digital HR can provide direct employee support, while AI should be used to strengthen knowledge creation, access, and sharing. Overall, the study highlights that digital technology provides the capability, but effective Knowledge Management converts that capability into meaningful employee engagement and improved hospitality outcomes.

This study contributes to digital HRM research by demonstrating that Digital HR and AI influence employee engagement through distinct pathways. Digital HR has both direct and KM-mediated effects on employee engagement, whereas AI has no significant direct effect and influences engagement fully through KM. These findings extend the JD-R Model and SDT by highlighting Knowledge Management as a proximal organisational resource through which technological capabilities can translate into employee-level outcomes. The findings also support SET by indicating that employee-oriented Digital HR practices can strengthen engagement through reciprocal organisational relationships. Evidence from the Nepalese hospitality sector further extends the applicability of these perspectives to a developing-country service context.

The findings indicate that hospitality organisations should integrate Digital HR and AI adoption with Knowledge Management rather than treating technology implementation as an end in itself. Digital HR systems should support employee learning, feedback, information access, and knowledge sharing, while AI applications should be designed to convert data and insights into accessible knowledge and development resources. The full mediation of KM in the AI–employee engagement relationship particularly suggests that AI investments are unlikely to improve engagement unless employees can effectively access and use the knowledge generated through these technologies. Strengthening KM infrastructure and knowledge-sharing practices can therefore help hotels translate digital investments into higher employee engagement and improved service delivery.

At the societal level, the findings highlight the importance of an employee-centred approach to digital transformation in Nepal's hospitality sector. Integrating AI and Digital HR with knowledge sharing and employee development can strengthen workforce capabilities, support digital skill development, and contribute to better service quality. Such an approach can help ensure that technological advancement creates value for both hospitality organisations and their employees.

The findings should be interpreted in light of several limitations. The cross-sectional design limits causal inference, while the convenience sample of hotel employees from Bagmati Province restricts the generalizability of the findings to other regions and service contexts. Furthermore, AI was operationalized as a single construct, and the quantitative design did not capture the contextual and experiential dimensions of technology adoption and knowledge sharing.

Future research should employ longitudinal designs to examine changes in these relationships over time and use larger, more diverse samples across Nepal and other service industries. Studies could also differentiate among AI applications, such as generative AI and algorithmic decision-making, and examine organisational culture, leadership, digital self-efficacy, and trust in technology as potential boundary conditions. Mixed-method approaches and additional outcomes, including service quality and turnover intention, could further clarify how digital technologies create employee and organisational value.

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Conflict of Interest

The author(s) declare that there is no conflict of interest.

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Data Availability Statement

The data supporting the study are available from the corresponding author upon reasonable request and subject to appropriate ethical and confidentiality considerations.

Authors Contributions

Sadhana Khati Chhetri: Literature Review, Data Collection, Investigation, Validation, Writing—Review and Editing, and Resources.

Renu Chaurasiya: Conceptualisation, Methodology, Data Collection, Data Analysis, Writing—Original Draft, and Visualisation.

Sudeep Ijam: Methodology, Data Collection, Software, Data Validation, Writing—Review and Editing, and Project Administration.

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Disclosure of Ai Use

The author used AI-based tools, including Grammarly for grammar checking and language refinement, and paraphrasing tools such as QuillBot to improve clarity and readability. These tools were used solely for linguistic enhancement. No generative AI tools were used to create original content, develop ideas, or conduct any part of the study. The author retains full responsibility for the accuracy, integrity, and originality of the manuscript.