Generative AI Usage, AI Literacy, and Employee Performance in Parsa's Industrial and Trading Enterprises

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ABSTRACT

Purpose: *Generative AI adoption is transforming organizational performance globally, yet its influence on employee outcomes depends heavily on AI literacy rather than usage alone.*

Methods: *Existing studies focus on corporate, educational, or Chinese contexts, leaving Nepal's industrial and trading sector, particularly Parsa District, unexplored. This quantitative study used Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0 and SPSS 20. Data were collected from 105 employees of Parsa's industrial and trading enterprises using convenience sampling.*

Results: *Generative AI Usage significantly predicts AI Literacy, which significantly predicts Employee Performance; however, the direct effect of Generative AI Usage on performance was non-significant, confirming full mediation. Field observations show limited practical AI literacy despite basic awareness, grounded in AMO and Social Cognitive theories. AI Literacy, not mere access, drives performance gains.*

Originality/Value: *This study validates the mediation model within Nepal's underexplored Terai-Madhesh context. Longitudinal and cross-sector studies are recommended to generalize these findings.*

Keywords: Generative AI usage, AI literacy, employee performance, PLS-SEM, Parsa district

JEL Classification: O33, J24, M15, L25

1. INTRODUCTION :

Globally, AI adoption has already transformed corporate finance, improving forecasting accuracy and risk management, underscoring AI's broader potential to reshape organizational performance (Celestin & Mishra (2025). [1]). Personality traits and organizational AI resource support enhance AI literacy, which subsequently improves work performance among South Korean employees (Lee & Jeon (2025). [2]). This aligns with prior findings that Madhesh Province's management education shows weak experiential learning and limited practical skill development, reinforcing the need for AI literacy interventions (Karn (2026). [3]). Similarly, shared positive attitudes toward generative AI within management teams stimulate AI-augmented collaborative strategizing, while negative attitudes undermine organizational effectiveness and firm performance (Vuori (2025). [4]). Similarly, digital transformation is reshaping job design across Nepal, though limited digital literacy and low AI adoption continue restricting effective job redesign and employee performance (Karn et al. (2026). [5]). Notably, generative AI adoption may widen performance gaps rather than reduce them, as high-performing employees leverage superior expertise and strategic AI deployment more effectively (Call et al. (2026). [6]). Similarly, Nepal's higher education system faces persistent challenges from delays, political interference, and memory-based assessment, highlighting the need for digital and competency-driven reforms (Karn et al. (2026). [7]). Including, AI literacy in academic practice can build a strong base to the future executives of business organizations.

GenAI's organizational value depends on employees' capacity to evaluate, interpret, and apply generated content effectively, beyond mere adoption or usage frequency (Yudhistyra, & Srinuan (2026). [8]). Although prior studies confirm that Generative AI Usage and AI Literacy positively influence Employee Performance, most originate from corporate, educational, or Chinese settings, leaving Nepal's industrial and trading sector, particularly Parsa District, largely unexplored. No study has empirically tested this mediation model within this region's distinct context using PLS-SEM. To address this gap, the study adopted a quantitative design, collecting data from 105 valid respondents through a structured questionnaire, analyzed using SPSS 20 and SmartPLS 4.0. Results confirm that Generative AI Usage significantly predicts AI Literacy, which in turn significantly predicts Employee Performance; however, the direct effect of Generative AI Usage on performance was non-significant, indicating full mediation through AI Literacy. Field observations reveal that while basic AI awareness exists among employees, practical literacy remains limited, restricting AI's strategic application. These findings show that AI Literacy, not mere tool access, drives performance. The novelty lies in validating this model within Nepal's underexplored Terai-Madhesh business context.

2. LITERATURE REVIEW :

Liu et al. (2025) [9] developed a validated Generative AI Literacy scale using AMO theory and found it significantly predicts job performance ($\beta = 0.680$), with Creative Self-Efficacy partially mediating this relationship (indirect effect = 0.537). This supports modeling AI literacy as a mediator between technology usage and employee performance outcomes. Zhang et al. (2026) [10] found that employees' cognitive and social use of GenAI tools significantly boosts innovative job performance, mediated by knowledge transfer, resource acquisition, and job satisfaction. This confirms GenAI usage drives performance outcomes indirectly through psychological and knowledge-based mechanisms, supporting mediation-based research designs. Sivathanu et al. (2026) [11] found self-directed learning, GAI literacy, perceived intelligence, and personalization positively influence self-efficacy, while technology anxiety negatively affects it. Self-efficacy significantly improves job performance, though hallucination potential weakens this relationship, supporting AI literacy's mediating role in performance outcomes. Cetindamar et al. (2024) [12] identified four core capabilities of employee AI literacy: technology-related, work-related, human-machine-related, and learning-related, emphasizing its operationalization for non-AI professionals in digital workplaces, supporting AI literacy as a multidimensional construct in this study. Koopmans et al. (2014) [13] identified four dimensions of individual work performance-task, contextual, adaptive performance, and counterproductive behavior-with task performance weighing 36%. This provides a validated, standardized framework for operationalizing the Employee Performance construct in this study. Liu et al. (2025) [14] found generative AI adoption positively influences job crafting (seeking resources, seeking challenges, optimizing demands), which mediates career commitment and shapes employee outcomes, with liking of AI moderating some paths. This supports GAI usage as a driver of positive workplace behavior. Mishra and Bhattarai (2025) [15] examined HRM practices in Nepal's Bara-Parsa Industrial Corridor, highlighting organizational cynicism, job burnout, and perceived organizational support as key factors affecting employee morale, and called for formalized HR systems-directly grounding this study's Parsa-based context in the local literature. Raut (2025) [16] surveyed 110 employees in Birgunj's three-star hotels, finding satisfaction with recruitment and training practices, using convenience sampling. This local Birgunj-based HRM study supports the sampling approach and regional context relevant to this article's Parsa/Madhesh setting. Sah (2025) [17] studied 70 teachers in Sarlahi, Madhesh Province, finding ambiguity about AI's impact on job security and trust, recommending targeted AI training to build confidence. This Madhesh-based study supports the need for context-specific AI literacy interventions in this region. Khanal (2025) [18] used PLS-SEM with 197 Nepali postgraduate students, finding Generative AI Literacy (0.516) positively predicts student engagement (0.266) and academic performance (0.209), with engagement mediating this relationship. This Nepal-based PLS-SEM study strongly supports the mediation methodology and AI literacy framework used here. Pandey and Bhusal (2024) [19] identified four

ChatGPT literacy skills-prompting, hooking, qualifying, and rhetorical situations-as essential for effective AI use. This Nepal-based study reinforces prompting literacy as a core, transferable dimension of AI literacy relevant beyond education contexts. Karn (2024) [20] found unfair remuneration, job insecurity, and inflation as major stressors among Birgunj private sector employees, proposing emotional intelligence and Buddhist philosophy as coping tools. This self-authored Birgunj-based study grounds the workplace context of this research. Gautam et al. (2025) [21] found human-AI collaboration significantly strengthens the effect of digital transformation on Green HRM (interaction $\beta = 0.25$, $p < 0.001$) in Nepal's community colleges, using SEM and fsQCA. This Nepal-based study supports human-AI collaboration as a performance-enhancing mechanism. Mishra et al. (2025) [22] argue AI adoption in HRM must remain human-centered, balancing technology with ethical standards, compassion, and employee engagement. This book supports the view that AI usage should enhance, not replace, human capabilities in employee performance contexts. Karn (2025) [23] found Buddhist principles of ethical conduct and mindfulness guide socio-economic development and business practices in Madhesh's border communities. This regional study supports the ethical-awareness dimension of AI literacy within Parsa's local cultural and business context.

2.1 Research GAP:

Although a growing body of literature confirms that Generative AI usage and AI literacy positively influence employee performance through mediating mechanisms such as self-efficacy, knowledge transfer, and engagement (Khanal (2025). [18]; Liu et al. (2025). [9]; Sivathanu et al. (2026). [11]; Zhang et al. (2026). [10], most of these studies have been conducted in large corporate, educational, or Chinese organizational settings, with limited attention to Nepal's industrial and trading sector, particularly enterprises operating in the Parsa/Bara-Parsa business environment. Existing Nepal-based studies (Gautam et al. (2025). [21]; Mishra & Bhattarai (2025). [15]; Raut (2025). [16]; Sah (2025). [17] have examined HRM practices, AI awareness, and digital transformation separately, but none have empirically tested a mediation model linking Generative AI Usage, AI Literacy, and Employee Performance specifically among employees of Parsa's industrial and trading enterprises. Moreover, while global studies (Cetindamar et al. (2024). [12]; Liu et al. (2025). [14] have conceptualized AI literacy as a multidimensional construct, its application using PLS-SEM within Nepal's Terai-Madhesh business context-characterized by a distinctive industrial, trading, and socio-cultural environment (Karn (2024). [20], Karn (2025). [23]) -remains unexplored. This study addresses this gap by empirically examining the mediating role of AI Literacy between Generative AI Usage and Employee Performance among employees of industrial and trading enterprises in Parsa District, Nepal, using SmartPLS4-based Structural Equation Modeling. Much of the emerging empirical evidence has originated from educational settings, large organizational contexts, and studies conducted outside South Asia, particularly China, with limited evidence from Nepal's industrial and trading sector.

2.2 Objectives of the Paper:

The specific research objectives related to the scope and framework of the paper include:

(1) To examine the direct effect of Generative AI Usage on AI Literacy among employees in Parsa's industrial and trading enterprises.
(2) To evaluate the direct influence of AI Literacy on Employee Performance within the industrial and trading sectors of Parsa District.
(3) To assess the direct impact of Generative AI Usage on Employee Performance in the context of Parsa's regional business environment.
(4) To investigate the mediating role of AI Literacy in the relationship between Generative AI Usage and Employee Performance using Partial Least Squares Structural Equation Modeling (PLS-SEM).

2.3 Theoretical Framework:

This study uses two theories to explain how Generative AI Usage affects Employee Performance through AI Literacy.

a) AMO Theory

Blumberg, and Pringle (1982) [24] Appelbaum et al. (2000) [25] says performance depends on three things: Ability, Motivation, and Opportunity. Here, AI Literacy is the "ability" employees gain from using Generative AI tools. Motivation is their willingness to use these tools at work. Opportunity is the access to AI tools available in Parsa's industrial and trading enterprises. All three together shape performance. This matches (Liu, Zhang, & Wei (2025) [9], who used AMO theory to show AI literacy predicts job performance.

b) Social Cognitive Theory

Bandura (2001) [26] explains the psychological link. It says self-belief (self-efficacy) drives performance. As employees become more skilled in using Generative AI, they feel more confident, and this confidence improves their work performance. Sivathanu et al. (2026) [11] and Khanal (2025) [18] both found similar patterns.

Together, these two theories support the idea that Generative AI Usage builds AI Literacy, which then boosts Employee Performance -the core mediation model tested in this study (H1-H4).

2.4 Conceptual Framework and Hypotheses:

This study's framework rests on Ability-Motivation-Opportunity (AMO) Theory (Blumberg & Pringle (1982). [24]; Appelbaum et al. (2000). [25]) and Social Cognitive Theory (Bandura (2001) [26]). Together, these theories suggest that using generative AI tools builds employees' AI literacy, which in turn strengthens their job performance. Based on this reasoning, the study proposes:

- H1: Generative AI Usage has a significant positive effect on Employee Performance. Employees using AI tools tend to work faster and more accurately.
- H2: Generative AI Usage has a significant positive effect on AI Literacy. Regular use builds practical AI skills over time.
- H3: AI Literacy has a significant positive effect on Employee Performance. Literate employees apply AI tools more effectively.
- H4: AI Literacy significantly mediates the relationship between Generative AI Usage and Employee Performance, translating AI use into improved performance outcomes.

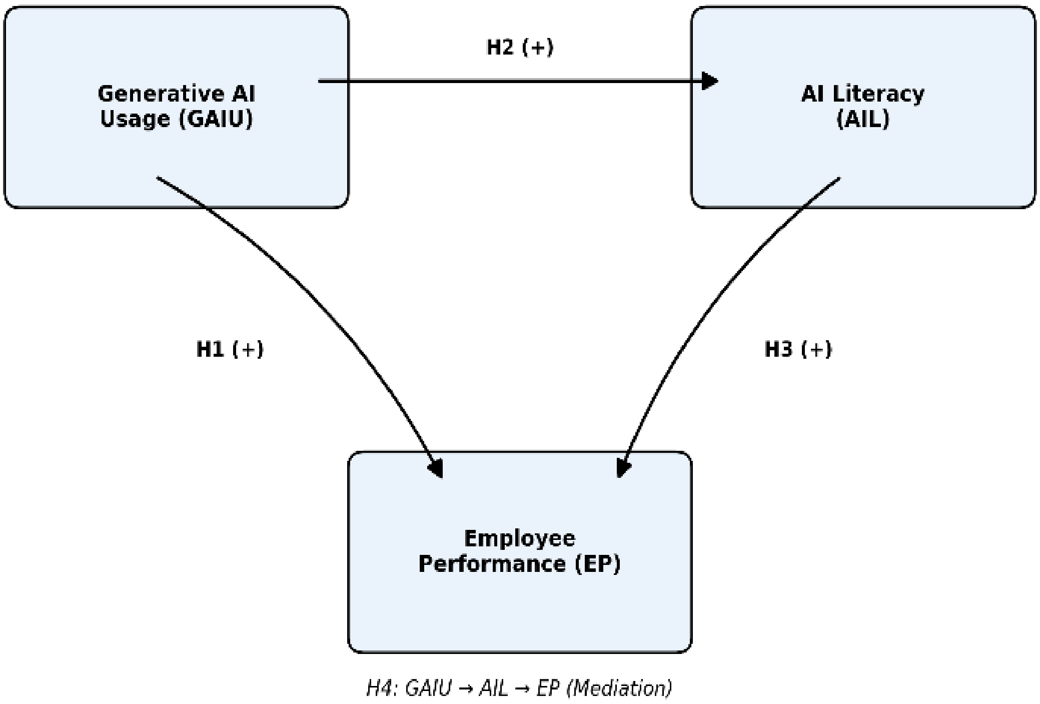

Fig. 1: Conceptual Framework

Note. Author's own construction (2026); Based on AMO Theory (Blumberg & Pringle, 1982; Appelbaum et al., 2000) and Social Cognitive Theory (Bandura, 2001).

As shown in Figure 1, Generative AI Usage (GAIU) is the independent variable, Employee Performance (EP) is the dependent variable, and AI Literacy (AIL) serves as the mediating variable. GAIU has a direct positive effect on AIL (H2) and EP (H1), while AIL also exerts a direct positive effect on EP (H3).

Together, these paths form the basis of the mediation hypothesis (H4), which proposes that AIL carries part of the effect of GAIU on EP.

3. METHODOLOGY :

This study adopted a quantitative research design using Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the relationship between Generative AI Usage, AI Literacy, and Employee Performance among employees of industrial and trading enterprises in Parsa District. Primary data were collected from 105 valid respondents through a structured questionnaire. SPSS 20 was used for preliminary data management, including demographic analysis and data screening, while SmartPLS 4.0 was employed for measurement and structural model assessment. The measurement model was evaluated through indicator loadings, internal consistency reliability (Cronbach's alpha, rho_a, rho_c), and convergent validity (Average Variance Extracted). Discriminant validity was confirmed using the Heterotrait-Monotrait ratio and the Fornell-Larcker criterion. The structural model was assessed using R^2 values, effect sizes (f^2), and path coefficients. Hypotheses were tested through a bootstrapping procedure with 5,000 resamples using the bias-corrected and accelerated (BCa) method, following standard PLS-SEM analytical guidelines.

The population comprised employees of industrial and trading enterprises in Parsa District. Using convenience sampling, 105 valid responses were collected through a structured questionnaire, meeting PLS-SEM's minimum sample size requirement and representing both industrial (63.8%) and trading (36.2%) enterprises.

4. RESULTS :

4.1 Respondents' Demographic Profile:

Table 1: Age Distribution of Respondents

Age Group	Frequency (n)	Percentage (%)
Below 25 years	49	46.7
25-35 years	31	29.5
35-44 years	25	23.8
Total	105	100.0

Note. Author's Calculation

Table 1 presents age distribution of respondents where nearly half of the respondents (46.7%) were below 25 years, followed by 29.5% aged 25-35 years and 23.8% aged 35-44 years.

Table 2: Gender Distribution of Respondents

Gender	Frequency (n)	Percentage (%)
Female	25	23.8
Male	74	70.5
Prefer not to say	6	5.7
Total	105	100.0

Note. Author's Calculation

Table 2 present gender distribution of respondents where, most respondents were male (70.5%), while 23.8% were female and 5.7% preferred not to disclose their gender.

Table 3: Educational Qualification of Respondents

Educational Qualification	Frequency (n)	Percentage (%)
Below Bachelor's level	31	29.5
Bachelor's degree	49	46.7
Master's degree	25	23.8
Total	105	100.0

Note. Author's Calculation

Table 3 present educational qualification of respondents where, most respondents held a bachelor's degree (46.7%), followed by those below bachelor's level (29.5%) and master's degree holders (23.8%).

Table 4: Enterprise Type of Respondents

Enterprise Type	Frequency (n)	Percentage (%)
Industrial enterprise	67	63.8
Trading enterprise	38	36.2
Total	105	100.0

Note. Author's Calculation

Table 4 represents types of enterprise of respondents where, most respondents (63.8%) were from industrial enterprises, while 36.2% were from trading enterprises, indicating greater representation of industrial-sector employees.

Table 5: Job Position of Respondents

Job Position	Frequency (n)	Percentage (%)
Assistant/Support staff	6	5.7
Middle management	24	22.9
Officer/Executive	31	29.5
Other	37	35.2
Supervisor	7	6.7
Total	105	100.0

Note. Author's Calculation

Table 5 present the job position of respondents where it is found that the largest group comprised respondents in other positions (35.2%), followed by officers/executives (29.5%) and middle management (22.9%).

Table 6: Work Experience of Respondents

Work Experience	Frequency (n)	Percentage (%)
Less than 1 year	31	29.5
1-3 years	18	17.1
4-6 years	12	11.4
7-10 years	32	30.5
More than 10 years	12	11.4
Total	105	100.0

Note. Author's Calculation

Table 6 describes the work experience of respondents where it is found that most respondents had 7-10 years of experience (30.5%), closely followed by those with less than one year (29.5%).

4.2 Measurement Model Assessment:

Table 7: Measurement Model — Item Loadings

Item	AIL	EP	GAIU
AIL3	0.654	-	-
AIL4	0.876	-	-
AIL5	0.731	-	-
EP1	-	0.796	-
EP2	-	0.832	-
EP3	-	0.516	-
EP4	-	0.629	-
EP5	-	0.898	-
GAIU1	-	-	0.498
GAIU2	-	-	0.559
GAIU3	-	-	0.788
GAIU4	-	-	0.975

GAIU5	-	-	0.762

Note. Author's Calculation; AIL = AI Literacy; EP = Employee Performance; GAIU = Generative AI Usage. Blank cells indicate the indicator does not load on that construct.

Table 7 presents the outer loadings of all measurement items across the three constructs. Most indicators exceeded the recommended 0.60 threshold, confirming adequate item reliability. GAIU1 (0.498) and GAIU2 (0.559), though slightly lower, were retained due to their contribution to content validity and acceptable construct-level AVE. Overall, the loadings support satisfactory indicator reliability for subsequent structural model assessment.

Table 8: Construct Reliability and Validity

Construct	Cronbach's α	rho_a	rho_c	AVE
AIL	0.647	0.679	0.801	0.576
EP	0.795	0.844	0.859	0.559
GAIU	0.835	1.420	0.849	0.543

Note. Author's Calculation; AIL = AI Literacy; EP = Employee Performance; GAIU = Generative AI Usage; rho_a = Composite Reliability (rho_a); rho_c = Composite Reliability (rho_c); AVE = Average Variance Extracted.

Table 8 reports internal consistency and convergent validity results. All constructs achieved composite reliability (rho_c) above 0.80, exceeding the 0.70 threshold. Average Variance Extracted (AVE) values exceeded 0.50 for all constructs (AIL = 0.576, EP = 0.559, GAIU = 0.543), confirming convergent validity. GAIU's rho_a (1.420) reflects a known estimation anomaly common in small samples, without affecting rho_c-based reliability conclusions.

Table 9: Discriminant Validity (Heterotrait-Monotrait Ratio)

Construct	AIL	EP	GAIU
AIL	—		
EP	0.658	—	
GAIU	0.508	0.239	—

Note. Author's Calculation; AIL = AI Literacy; EP = Employee Performance; GAIU = Generative AI Usage. All HTMT values are below the conservative threshold of 0.85, confirming discriminant validity.

Table 9 presents discriminant validity using the Heterotrait-Monotrait Ratio (HTMT). All HTMT values (AIL-EP = 0.658, AIL-GAIU = 0.508, EP-GAIU = 0.239) fall below the conservative threshold of 0.85, indicating that each construct is empirically distinct from the others. These results confirm adequate discriminant validity, supporting the appropriateness of treating GAIU, AIL, and EP as separate latent constructs in the structural model.

Table 10: Discriminant Validity (Fornell-Larcker Criterion)

Construct	AIL	EP	GAIU
AIL	0.759		
EP	0.529	0.748	
GAIU	0.463	0.185	0.737

Note. Author's Calculation; AIL = AI Literacy; EP = Employee Performance; GAIU = Generative AI Usage. Diagonal values represent the square root of AVE and exceed the off-diagonal inter-construct correlations, confirming discriminant validity.

Discriminant validity was further confirmed through the Fornell-Larcker criterion. The square root of AVE for each construct (AIL = 0.759, EP = 0.748, GAIU = 0.737) exceeded its correlations with other constructs. This pattern, consistent with the HTMT results, verifies that AIL, EP, and GAIU represent conceptually distinct constructs, strengthening confidence in the overall measurement model's validity.

4.3 Structural Model Assessment:

Table 11: Coefficient of Determination (R^2)

Construct	R^2	R^2 Adjusted
AIL	0.214	0.207
EP	0.285	0.270

Note. Author's Calculation; AIL = AI Literacy; EP = Employee Performance. R^2 values indicate the proportion of variance explained in each endogenous construct.

The structural model explained 21.4% of the variance in AI Literacy ($R^2 = 0.214$) and 28.5% of the variance in Employee Performance ($R^2 = 0.285$). Following Chin's (1998) guidelines for social science research, these values indicate weak-to-moderate explanatory power, acceptable given the exploratory nature of the study and the multifactorial determinants of employee performance beyond generative AI usage.

Table 11: Effect Size (f^2)

Construct	AIL	EP	GAIU
AIL		0.350	
EP			
GAIU	0.273	0.006	

Note. Author's Calculation; AIL = AI Literacy; EP = Employee Performance; GAIU = Generative AI Usage. Following Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively.

Effect size analysis revealed that AIL exerted a large effect on EP ($f^2 = 0.350$) and GAIU exerted a large effect on AIL ($f^2 = 0.273$), while GAIU's direct effect on EP was negligible ($f^2 = 0.006$). These results reinforce the mediation pathway, indicating that GAIU's influence on EP operates substantially through AIL.

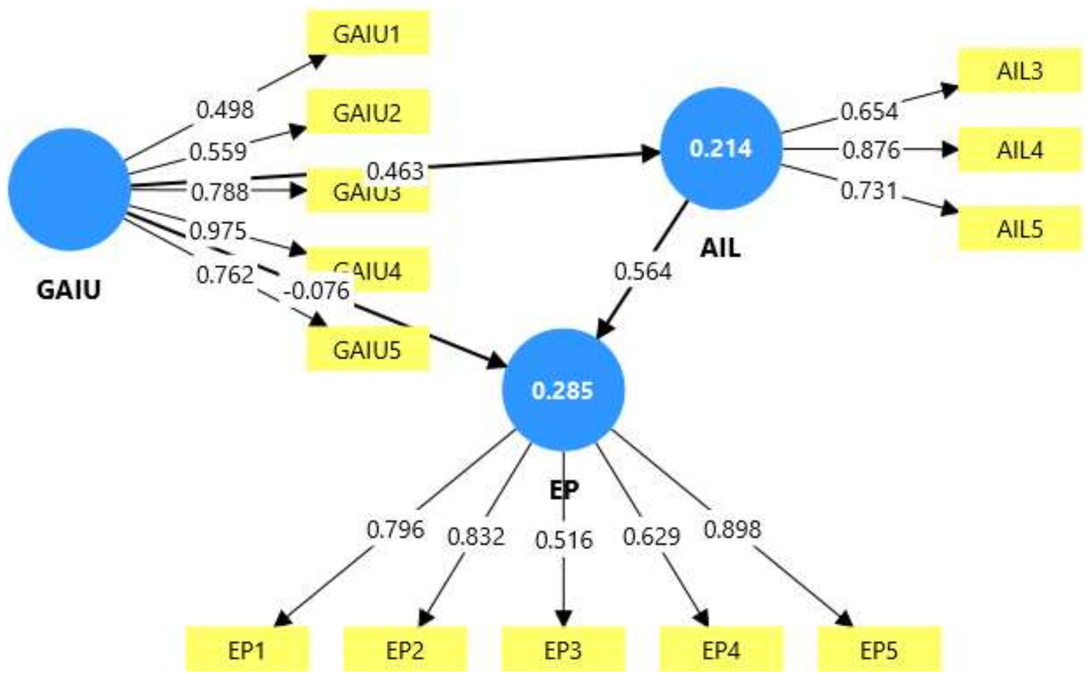

Fig. 2: Structural Model with Path Coefficients and R^2

Note. Author's SmartPLS4 output (2026).

Figure 2 displays the estimated structural model showing standardized path coefficients and R^2 values for endogenous constructs. Generative AI Usage positively predicts AI Literacy ($\beta = 0.463$), which in turn predicts Employee Performance (β = 0.564). The direct path from GAIU to EP (β = -0.076) is weak, visually suggesting that AI Literacy plays the dominant explanatory role in the model.

4.4 Hypothesis Testing:

Table 12: Hypothesis Testing Results (Direct Effects)

Path	O	M	STDEV	T Statistics	P Values
H1: GAIU → AIL	0.463	0.497	0.100	4.611	0.000
H2: AIL → EP	0.564	0.587	0.075	7.543	0.000
H3: GAIU → EP	-0.076	-0.071	0.099	0.768	0.442

Note. Author's Calculation; AIL = AI Literacy; EP = Employee Performance; GAIU = Generative AI Usage; O = Original Sample; M = Sample Mean; STDEV = Standard Deviation. Bootstrapping based on 5,000 subsamples (BCa method). $p < .05$ indicates statistical significance.

Bootstrapping results (5,000 resamples, BCa method) confirmed that GAIU significantly predicts AIL (β = 0.463, t = 4.611, $p < .001$), supporting H1. AIL significantly predicts EP (β = 0.564, t = 7.543, $p < .001$), supporting H2. However, the direct effect of GAIU on EP was non-significant (β = -0.076, t = 0.768, p = .442), leading to the rejection of H3.

Table 13: Mediation Analysis (Specific Indirect Effect)

Path	O	M	STDEV	T Statistics	P Values
H4: GAIU → AIL → EP	0.261	0.294	0.079	3.291	0.001

Note. Author's Calculation; AIL = AI Literacy; EP = Employee Performance; GAIU = Generative AI Usage; O = Original Sample; M = Sample Mean; STDEV = Standard Deviation. Bootstrapping based on 5,000 subsamples (BCa method). The significant indirect effect, combined with the non-significant direct effect (Table 7, H3), indicates full mediation of AIL between GAIU and EP.

Mediation analysis revealed a significant specific indirect effect of GAIU on EP through AIL (β = 0.261, t = 3.291, p = .001), supporting H4. Given that the direct effect (H3) was non-significant while the indirect effect was significant, the results indicate full mediation, confirming that AI Literacy fully explains the mechanism through which Generative AI Usage translates into improved Employee Performance.

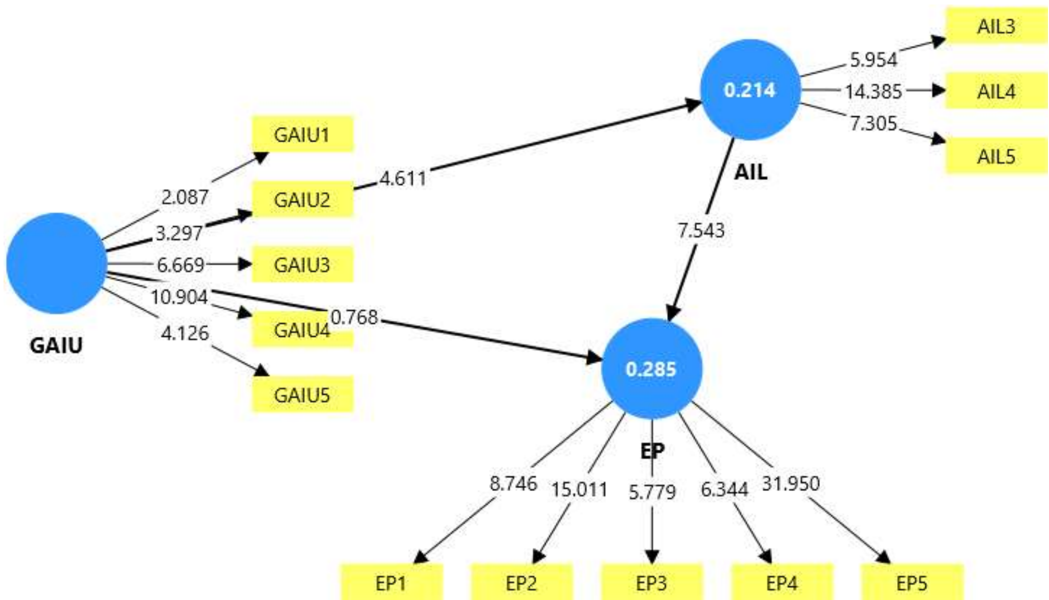

Fig. 3: Bootstrapped Structural Model (T-Statistics)

Note. Author's SmartPLS4 output (2026), based on 5,000 bootstrap subsamples (BCa method).

Figure 3 displays the bootstrapped structural model with t-statistics for all paths and item loadings, generated from 5,000 bootstrap subsamples using the BCa method. The GAIU→AIL ($t = 4.611$) and AIL→EP ($t = 7.543$) paths exceed the critical value of 1.96, confirming significance, while the GAIU→EP direct path ($t = 0.768$) falls below this threshold, visually corroborating the non-significant direct effect.

The findings show that Generative AI Usage significantly predicts AI Literacy ($\beta = 0.463$, $p < .001$), supporting H1, and AI Literacy significantly predicts Employee Performance ($\beta = 0.564$, $p < .001$), supporting H2. However, the direct path from Generative AI Usage to Employee Performance was not significant ($\beta = -0.076$, $p = .442$), rejecting H3. The significant indirect effect ($\beta = 0.261$, $p = .001$) confirms H4, indicating that AI Literacy fully mediates this relationship.

5 DISCUSSION :

Field observations from Parsa District provide useful context for interpreting the study’s findings. Industrial, trading, and service-oriented enterprises in the district continue to rely on traditional business practices, even though computer systems, particularly accounting and financial management software, have been in use for nearly a decade or more. The trading sector shows a stronger presence in terms of business count, while industrial enterprises contribute significantly through transaction volume and scale of operations. Despite the growing global relevance of Artificial Intelligence, its actual use in accounting, reporting, and Management Information Systems within these organizations remains minimal. Employees demonstrated basic familiarity with popular AI tools such as ChatGPT, Claude, Perplexity, and Canva, but these were mainly applied for simple tasks like information searching, content preparation, and design work, rather than for strategic planning, forecasting, or organizational decision-making. This pattern suggests that AI is often treated as a substitute for conventional search engines rather than as a tool for enhancing productivity and performance. Notably, younger employees were not entirely unaware of AI; however, a clear gap exists between general awareness and the practical literacy needed to apply AI meaningfully at work. Organizations also appear to lack systematic investment in employee training and AI-related capability building. These observations reinforce the study’s core finding that AI Literacy plays a critical mediating role: without adequate literacy, exposure to Generative AI tools alone does not translate into improved Employee Performance, highlighting the need for structured, organization-level AI literacy initiatives in Parsa’s business environment.

This study examined Generative AI Usage, AI Literacy, and Employee Performance in Parsa’s industrial and trading enterprises, testing a mediation model grounded in AMO Theory and Social Cognitive Theory. The results confirm that Generative AI Usage significantly builds AI Literacy (H1), and AI Literacy, in turn, significantly improves Employee Performance (H2). However, Generative AI Usage alone does not directly enhance performance (H3 rejected); rather, its effect operates entirely through AI Literacy, as confirmed by the significant indirect effect (H4). This pattern of full mediation indicates that simply having access to AI tools is insufficient for performance gains unless employees also develop the skills and confidence to apply them meaningfully.

These statistical findings align closely with field observations from Parsa District. Although computer-based accounting and financial systems have been used for over a decade, AI adoption for strategic, managerial, and operational purposes remains limited. Employees, particularly younger ones, showed awareness of common AI tools such as ChatGPT, Claude, and Canva, but mostly used them for basic tasks like information searching and content creation rather than decision-making or productivity enhancement. This gap between awareness and applied literacy directly explains why Generative AI Usage alone failed to predict performance, while AI Literacy emerged as the critical mechanism.

Together, these results support the AMO framework, where ability (AI Literacy) determines whether opportunity (AI access) translates into motivation-driven performance outcomes, consistent with Social Cognitive Theory’s emphasis on self-efficacy. The findings suggest that organizations in Parsa cannot rely on AI tool availability alone; they must invest systematically in employee training and literacy development. Nepal’s contemporary business environment similarly requires contextual adaptation of management practices, balancing efficiency with human-centric approaches (Karn et al. (2026). [27]). Without such investment, the transformative potential of Generative AI in industrial and trading enterprises will remain largely unrealized, limiting both individual performance and broader organizational competitiveness in an increasingly AI-driven business environment.

In countries like Nepal, Artificial Intelligence (AI) is mainly viewed as a specialized tool used for research, education, teaching, official work, and other professional activities. Nepal, as a developing country, largely depends on externally developed AI technologies, which often require organizations and institutions to pay for subscriptions or services in foreign currency. In contrast, developed countries have stronger capabilities to develop and produce AI technologies domestically. Therefore, organizations in such countries may have easier access to advanced AI technologies and can integrate them from management information systems to operational-level activities.

In Nepal, particularly in districts such as Parsa, AI is still an advanced component of digital transformation. Organizations, industries, trading firms, and educational institutions may need to make significant financial investments to acquire AI tools, multiple versions, user accounts, training, and related services. As a result, AI adoption can become an additional organizational investment rather than simply a technological tool. Across Nepal, including industrial, trading, educational, service, and government sectors, AI is currently used mainly as an acquired technology. Most users are still learning how to apply AI for different tasks, while domestic AI development and creation remain at an emerging stage. This situation creates challenges for wider and more advanced organizational AI adoption.

6. CONCLUSION :

This study confirms that AI Literacy fully mediates the relationship between Generative AI Usage and Employee Performance among employees of industrial and trading enterprises in Parsa District, Nepal. While Generative AI Usage significantly builds AI Literacy, and AI Literacy significantly improves Employee Performance, Generative AI Usage alone does not directly enhance performance. This indicates that mere access to AI tools is insufficient; employees must also develop practical literacy to apply these tools meaningfully. Field observations reinforce this finding, revealing that although basic AI awareness exists among employees, structured training and organizational investment remain limited. Grounded in AMO Theory and Social Cognitive Theory, the study highlights those Nepalese organizations, particularly in Parsa's business environment, must prioritize systematic AI literacy development to fully realize Generative AI's performance-enhancing potential.

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