

AI Literacy and Academic Performance among Non-STEM Students in KNUST: The Roles of LMS Quality and Blended-Learning Satisfaction

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Research Article

Keywords: AI literacy, blended learning, LMS quality, learning satisfaction, academic performance, PLS-SEM, non-STEM, Ghana

Posted Date: October 5th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11239563/v1>

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Additional Declarations: No competing interests reported.

AI Literacy and Academic Performance among Non-STEM Students in KNUST: The Roles of LMS Quality and Blended-Learning Satisfaction

Abstract

With the growing integration of AI in higher education, it remains unclear how AI literacy relates to academic performance among non-STEM students. This study examined the sequential mediating roles of learning management system (LMS) quality and blended-learning satisfaction (BLS) in the relationship between AI literacy and academic performance. 432 students from the non-STEM at Kwame Nkrumah University of Science and Technology in Ghana participated in a quantitative cross-sectional survey. Partial least squares structural modelling (PLS-SEM) in SmartPLS 4 was used for the data analyses. AI literacy strongly predicted LMS quality ($\beta = .814, p < .001$) and showed a notably significant effect on academic performance ($\beta = .222, p = .001$). The LMS quality significantly predicted BLS ($\beta = .604, p < .001$), which then predicted academic performance ($\beta = .535, p < .001$). LMS quality did not significantly influence academic performance ($\beta = .074, p = .233$). It did not independently mediate the correlation between AI literacy and academic performance ($\beta = .061, p = .236$). In contrast, in a direct sequential pathway, LMS quality proved significant ($\beta = .263, p < .001$). University policymakers should support students with blended learning support and organise AI literacy training in addition to funding digital infrastructure. AI literacy strongly correlates with academic performance when digital systems are built to support rewarding blended learning experiences.

Keywords: AI literacy; blended learning; LMS quality; learning satisfaction; academic performance; PLS-SEM; non-STEM; Ghana

1.0 Introduction

Artificial Intelligence (AI) has moved from the outer limits to the foundation of higher education instructional frameworks via AI-driven analytics, adaptive systems, and intelligent tutoring platforms (Lampou et al., 2026; F. Zhang et al., 2025), promoting personal learning and inclusivity (Khalid et al., 2026) while also provoking concerns about algorithmic bias, academic integrity, privacy, and excessive dependence (AlBlooshi, 2026; Tomaylla-Quispe et al., 2025). AI literacy is characterised by students' proficiency in the technical, cognitive, ethical, and practical aspects of AI-enabled tools (Bećirović et al., 2025). The abilities to derive values from these affordances is contingent upon AI literacy, a complex construct which includes technical, ethical, practical, social, creative and, cognitive skills (Hackl et al., 2026; Ruhi et al., 2025; Wang et al., 2023) and serves as a significant predictor of academic performance (Bećirović et al., 2025; Yilmaz Soylu et al., 2025), although its development requires institutional assistance that is inequitably allocated globally (Ajani et al., 2025; Angwaomaodoko, 2025; Fajarianto et al., 2025)

These capabilities are applied within a blended learning framework. The intentional incorporation of online and face-to-face education (Garrison & Vaughan, 2008; Graham, 2006; Istenič, 2024), has been expedited in the aftermath of the pandemic (Hill & Smith, 2023; Sareen & Mandal, 2025), with satisfaction recognised as a comprehensive construct encompassing infrastructure, instruction, materials, responsiveness, and peer interaction (Chen et al., 2023; Hassan et al., 2024; Panigrahi et al., 2024). The IS Success Model articulated by DeLone and McLean (2003) argues that Learning Management Systems impact satisfaction and performance through their information systems and service qualities (Al-Fraihat et al., 2020; Alzahrani & Seth, 2021; Chen & Wu, 2025; Herrera et al., 2025). As platforms increasingly migrate to adaptive delivery (Petrovic & Jaksic, 2026), using these systems requires a deeper understanding of AI and a commitment to algorithmic transparency (Abdullahi, 2025; Al-Abdullatif & Alsubaie, 2024; X. Zhang et al., 2025). The IS Success Model measures system quality through users' evaluations of usability, reliability and functionality (Al-Fraihat et al., 2020; DeLone & McLean, 2003), and such evaluations partly reflect what users can do with a system. Ai et al. (2026) and Shafiq et al. (2026) state that LMS seem easier to use and more reliable when users are proficient in AI literacy, which entails understanding, purposefully using and analysing AI-enabled systems (Long & Magerko, 2020; Ng et al., 2021). Learning management systems currently incorporate adaptive, analytical, and feedback functions. Students' impressions of these platforms are shaped by these features (Saqr et al., 2024). AI literacy mitigates anxiety while improving self-efficacy, which raises perceived usage across all fields of study (Getenet et al., 2024). In light of this, it is more accurate to think of AI literacy as a user-side predictor of perceived rather than objective LMS quality

Previous studies have examined LMS and AI literacy as separate predictors (Singh et al., 2024) or have established direct connections between AI literacy and performance mechanisms (Asghar et al., 2025). This raises the question of whether LMS quality mediates the impact of AI literacy on satisfaction and performance, a relationship that remains unexamined.

Satisfaction remains inadequately defined beyond binary metrics (Chen et al., 2023), and no cohesive model integrates these constructs (Hua et al., 2024; Kok et al., 2025). Studies tend to primarily focus on the STEM cohort within high-income contexts (Laupichler et al., 2022; Yang & Lay, 2024), overlooking the unique computational training, epistemologies, and satisfaction profiles of non-STEM students (Carolus et al., 2023; Kuskova et al., 2026; Nguyen et al., 2025; Shaban & Ali, 2026). This gap is particularly evident in Sub-Saharan Africa (Kiemde & Kora, 2022), where non-STEM students in Ghana reported minimal engagement with AI, despite significant enrolment figures (Angwaomaodoko, 2025; Asamoah & Amarteifio, 2025; Bervell et al., 2025; Tabiri et al., 2026).

Findings on AI literacy and performance remains contradictory. Studies such as (Shi et al., 2025; Singh et al., 2024) reported a positive correlation between AI literacy and performance, while others (Bancoro, 2024; Bećirović et al., 2025; Widowati et al., 2023) reported no significant direct correlation between AI literacy and academic performance, indicating that while literacy is essential, it may not be adequate on its own. Similarly, the impact of blended learning and the correlation between satisfaction and performance vary, and the literature lacks comprehensive synthesis across disciplines (Kyei-Akuoko et al., 2025; Müller et al., 2023). Addressing these gaps requires rigorous operational accuracy. This study investigates the interrelationships between AI literacy, BLS, and LMS quality, and their collective impact on academic performance among non-STEM higher education students in Ghana.

1.1 Research question and hypotheses

To address the identified gaps in the literature, the study posed four crucial research questions

1. To what extent does AI literacy influence LMS quality among non-STEM students?
2. To what extent does LMS quality influence blended-learning satisfaction?
3. To what extent does blended-learning satisfaction influence academic performance?

4. To what extent do LMS quality and blended-learning satisfaction mediate the relationship between AI literacy and academic performance?

Using the IS Sucees Model on existing research on AI literacy and Blended learning, these hypotheses were developed for non-STEM students in the blended learning context

H₁: AI literacy positively predicts perceived LMS quality.

H₂: LMS quality positively predicts blended-learning satisfaction.

H₃: Blended-learning satisfaction positively predicts academic performance.

H₄: Perceived LMS quality positively predicts academic performance.

H₅: AI literacy positively predicts academic performance.

H₆: LMS quality mediates the relationship between AI literacy and academic performance.

H₇: LMS quality and blended-learning satisfaction sequentially mediate the relationship between AI literacy and academic performance

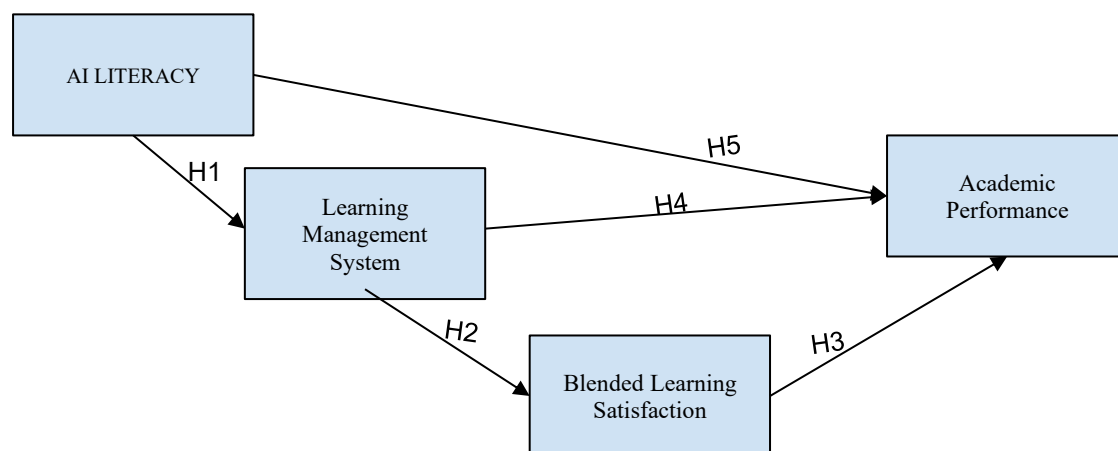


Fig 1: Conceptual Framework

2. Research Methodology

2.1 Research Design and Setting

A quantitative cross-sectional survey examined the structural relationships among AI literacy, LMS quality, blended learning satisfaction, and academic performance. This design aligned with the study's emphasis on concurrent perceptual relationships; however, it cannot establish temporal precedence. Data were collected from both graduate and undergraduate students

within the Teacher Education and Educational Innovation in Science and Technology (EIST) departments at KNUST, Ghana. KNUST provides a blended learning instructional approach using a Virtual classroom, an open-source learning management system that hosts course materials, facilitates asynchronous discussion, and conducts assessment in conjunction with in-person sessions. The institution's large cohorts and limited instructor-to-student ratio, typical of public universities in sub-Saharan Africa, make it an appropriate setting for investigating the boundary of the AI literacy-LMS framework.

2.2 Population, Sampling, and Sample Size Determination

The target population comprised undergraduate and graduate students enrolled in blended-delivery courses at KNUST during 2025/2026. Using Soper's (2026) a priori calculator (effect size = 0.3, α = .05, power = .90, four latent variables, 21 observed variables), the minimum required sample was 173, raised to 190 after a 10% attrition inflation (Das & Datta, 2024). The achieved sample of 450 exceeded both thresholds and the conventional 0.80 power benchmark, reducing the risk of Type II error in the hypothesis tests.

Convenience sampling recruited accessible participants from a relatively homogeneous population, valued for practicality and prevalence in theory-testing research (Nurzhanova et al., 2024). Although it limits representativeness, it can yield reliable results when appropriately managed.

2.3 Data Collection and Screening

Participants completed the survey voluntarily via QR code, following a briefing on the study's objectives and the voluntary, confidential nature of participation. Participants completed 450 questionnaires. Outliers were identified using standardised z-scores, with cases exceeding ± 3 SD flagged as extreme; 18 such cases were excluded, yielding 432 valid cases with no missing values and normally distributed items.

2.4 Instrumentation

The questionnaire comprised 21 items across four constructs: AI literacy (AILS, 12 items; Wang et al., 2023), LMS quality (3 items), and blended-learning satisfaction and academic performance (3 items each; Zeqiri et al., 2021), on a six-point Likert scale. Reliability ranged $\alpha = .82-.89$.

2.5 Ethical Considerations

The Humanities and Social Science Research Ethics Committee, KNUST (HuSSREC/AP/261/VOL.4), granted ethical approval in accordance with the Declaration of Helsinki.

2.6 Data Analysis

PLS-SEM in SmartPLS 4 was used for the analysis. PLS-SEM was used because of its causal predictive orientation, its ability to handle complex models with multiple indirect paths, and its resilience when dealing with non-normal data (Hair et al., 2019). It was also used alongside Importance-Performance Map Analysis. The IPMA examines total effects and construct performance scores

3.0 Results

3.1 Common Method Bias.

Common method bias was evaluated using the full collinearity test, with a VIF threshold of 3.3 (Kock, 2015). BLS→AP (2.2) and LMS→AP (2.9) passed, but AI Literacy→AP (4.093, 95% CI [3.327, 4.938]) exceeded 3.3, so method bias cannot be excluded. All VIFs were below the critical collinearity threshold of 5 (Hair et al., 2019).

3.2 Measurement Model Assessment.

The measurement model satisfied the established criteria for reliability and validity. Indicator loadings ranged from .705 to .911, with 19 out of the 21 indicators surpassing the .708 threshold (Hair et al., 2019). The two exceptions, AI lit_1 (.707) and AI lit_10 (.705), were retained as they fell only marginally short, with construct reliability and convergent validity remaining satisfactory. Internal consistency was confirmed, with values for α , ρ_a , and ρ_c all exceeding

.80 and remaining below the .95 redundancy threshold. Additionally, the average variance extracted (AVE) for each construct exceeded the .50 mark (Hair et al., 2019). The comparatively lower AVE of AI Literacy (.538) indicates moderate loadings across 12 indicators. Discriminant validity was evaluated using the HTMT ratio, with a .90 threshold for the conceptually related constructs (Hair et al., 2019; Henseler et al., 2015). This threshold is suitable as both satisfaction and performance evaluate the same blended learning experience, while AI literacy and LMS quality pertain to engagement with digital learning technologies. All HTMT values were below .90, and no percentile bootstrap confidence interval (10,000 subsamples) encompasses 1.00 (Henseler et al., 2015). Nonetheless, the upper bounds for BLS↔AP (95% CI [.817, .954]) and LMS↔AI literacy (95% CI [.850, .928]) surpassed .90. Discriminant validity is thus affirmed, even though these two pairs showed considerable variance.

Table 1: Measurement Model: Outer Loadings, Reliability, and Convergent Validity

Construct	Item	Loading	Cronbach's α	ρ_a	ρ_c	AVE
AI Literacy	AI Lit_1	.707	.922	.923	.933	.538
	AI Lit_2	.750				
	AI Lit_3	.728				
	AI Lit_4	.742				
	AI Lit_5	.726				
	AI Lit_6	.785				
	AI Lit_7	.732				
	AI Lit_8	.742				
	AI Lit_9	.714				
	AILit_10	.705				
	AILit_11	.737				
	AILit_12	.731				
LMS	LMS_1	.909	.891	.891	.932	.821
	LMS_2	.911				
	LMS_3	.898				
Blended-Learning Satisfaction	BLS_1	.877	.806	.812	.885	.720
	BLS_2	.844				
	BLS_3	.824				
Academic Performance	AP_1	.900	.864	.866	.917	.787
	AP_2	.886				
	AP_3	.875				

Table 2: Heterotrait-Monotrait Ratio (HTMT) with 95% Bootstrap Confidence Intervals

Construct pair	HTMT	95% CI
BLS ↔ AI Lit_	.835	[.765, .895]
BLS ↔ AP_	.884	[.817, .945]
LMS ↔ AI Lit_	.892	[.850, .928]

LMS ↔ AP_	.657	[.556, .745]
LMS ↔ BLS	.711	[.617, .796]
AP_ ↔ AI Lit_	.746	[.667, .814]

3.3 Coefficient of Determination (R^2 and Adjusted R^2)

R^2 and adjusted R^2 were utilised to assess the explanatory power of each endogenous construct, with values of .75, .50, and .25 considered substantial, moderate, and weak, respectively (Hair et al., 20219). LMS showed moderate explanatory power, nearing the substantial threshold ($R^2 = .663$), followed by Academic performance ($R^2 = .590$), and blended learning satisfaction ($R^2 = .365$). The minimal gap between R^2 and adjusted R^2 suggest a stable explanatory power that is not influenced by the number of predictors (Hair et al., 2019; Sarstedt et al., 2023)

Table 3: Coefficient of Determination (R^2 and Adjusted R^2)

Construct	R^2	Adjusted R^2
AP_	.590	.587
BLS	.365	.364
LMS	.663	.662

3.4 Effect Size (f^2)

The thresholds of .02 (minor), .15 (moderate), and .35 (substantial) effects (Hair et al., 2019), AI literacy significantly affected LMS quality ($f^2 = 1.963$) and had a negligible influence on academic performance ($f^2 = .030$). LMS quality influenced BLS significantly ($f^2 = .576$), BLS moderately influenced academic performance ($f^2 = .326$), and LMS quality had a minimal effect on academic performance

Table 4: Effect Sizes (f^2) for Structural Paths

Path	f^2
AI Lit_ → AP_	.030
AI Lit_ → LMS	1.963
BLS → AP_	.326
LMS → AP_	.005
LMS → BLS	.576

3.5 Predictive Relevance

The PLS prediction outside the sample was assessed. According to Hair et al. (2019), the model performed better than the uniform threshold for indicator means, since all endogenous

constructs had positive Q^2 values. LMS ($Q^2=.660$), Blended learning satisfaction ($Q^2=.472$), and Academic performance ($Q^2=.430$).

Table 5: PLSpredict Latent Variable Summary

Construct	Q^2_{predict}	RMSE	MAE
LMS	.660	.588	.432
BLS	.472	.733	.560
AP	.430	.763	.563

3.6 Structural Model Analysis

PLS-SEM was utilised to estimate the structural model of AI literacy, LMS, BLS, and Academic performance. AI literacy significantly predicted LMS ($\beta = .814$) and moderately predicted AP ($\beta = .222$). LMS strongly predicted BLS ($\beta = .604$), which predicted AP ($\beta = .535$), while LMS's direct effect on AP was moderate ($\beta = .074$), suggesting BLS mediated this correlation (Sarstedt et al., 2023). The model explains modest variance in AP ($R^2 = .663$), AP_ ($R^2 = .590$), and BLS ($R^2 = .365$) (Hair et al., 2019).

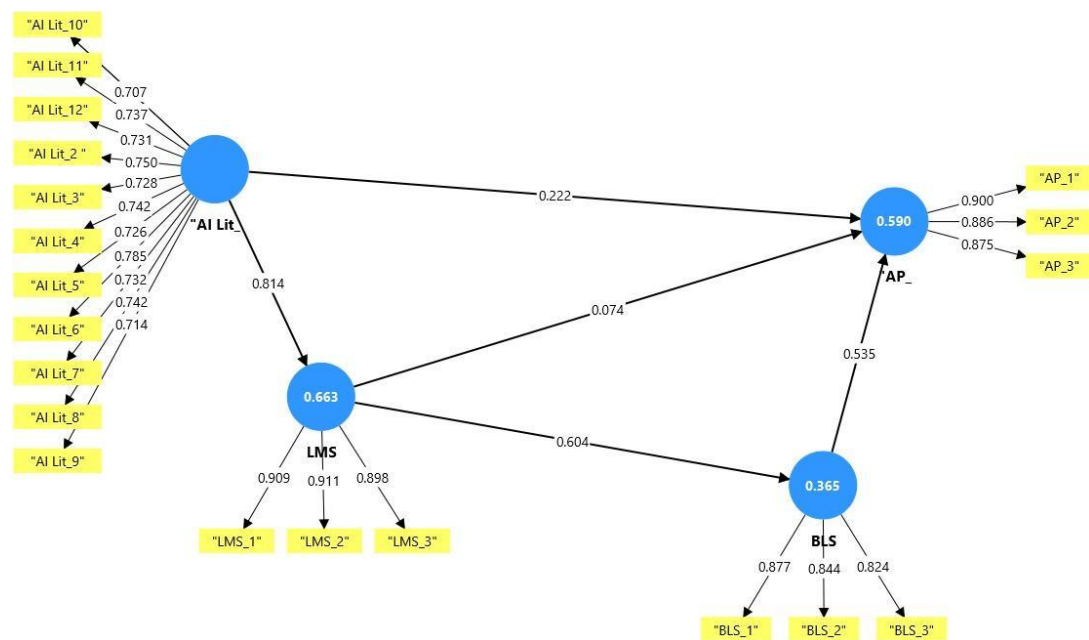


Figure 2: Structural model

3.7 Hypothesis Testing (Direct Effects)

The hypotheses were analysed using 10,000 bootstrapped subsamples. Four of the five direct paths were statistically significant. H01 was rejected because AI literacy significantly predicted LMS quality ($t = 42.050$, $p < .001$). H02 was rejected as LMS quality significantly predicted Blended learning satisfaction ($t = 14.824$, $p < .001$). H03 was rejected because blended learning satisfaction strongly predicted Academic performance ($t = 8.505$, $p < .001$). H05 was rejected because AI literacy strongly predicted academic performance ($t = 3.394$, $p = .001$). H04 was not rejected: the direct LMS quality–academic performance path was not significant ($t = 1.192$, $p = .233$).

Table 7: Hypothesis Testing — Bootstrapped Path Coefficients

Path	β (O)	M	SD	t- statistic	p	Decision
AI literacy → LMS quality	.814	.815	.019	42.050	< .001	Supported
LMS quality → blended-learning satisfaction	.604	.605	.041	14.824	< .001	Supported
Blended-learning satisfaction → academic performance	.535	.534	.063	8.505	< .001	Supported
LMS quality → academic performance	.074	.072	.062	1.192	.233	Not supported
AI literacy → academic performance	.222	.225	.065	3.394	.001	Supported

3.8 Mediation Analysis (Specific Indirect Effects)

Indirect effects from 10,000 bootstrap subsamples are seen in Table 8. There was a strong correlation between AI literacy, LMS quality, and blended-learning satisfaction ($t = 7.038$, $p < .001$), supporting H07 that blended-learning satisfaction mediates the association between AI literacy and academic achievement. LMS quality alone did not influence the shorter indirect pathway from AI literacy to academic achievement ($t = 1.185$, $p = .236$), disproving H06. The substantial relationship between LMS quality, blended-learning satisfaction, and academic achievement ($t = 7.529$, $p < .001$) highlights the importance of satisfaction as a mediator.

Table 8: Hypothesis Testing — Specific Indirect Effects

Path	β (O)	M	SD	t- statistic	p	Decision
AI literacy → LMS quality → blended-learning satisfaction	.492	.493	.039	12.548	< .001	Supported
LMS quality → blended-learning satisfaction → academic performance	.324	.323	.043	7.529	< .001	Supported

AI literacy → LMS quality → blended-learning satisfaction → academic performance	.263	.263	.037	7.038	< .001	Supported
AI literacy → LMS quality → academic performance	.061	.059	.051	1.185	.236	Not supported

3.9 Importance-Performance Map Analysis (IPMA)

Importance Performance Map Analysis (IPMA) was used to determine priority constructs by analysing importance (total effects) and performance (mean latent variable scores) (Hair et al., 2019). At .546, AI literacy was the most important, but it performed poorly at 71.237. Blended learning satisfaction scored 75.857, while the Learning management system (LMS) scored .398, suggesting poor priority

Table 9: Importance-Performance Map Analysis for Academic Performance (AP)

Construct	Importance (total effect)	Performance
AI Lit_	.546	71.237
BLS	.535	75.857
LMS	.398	73.544

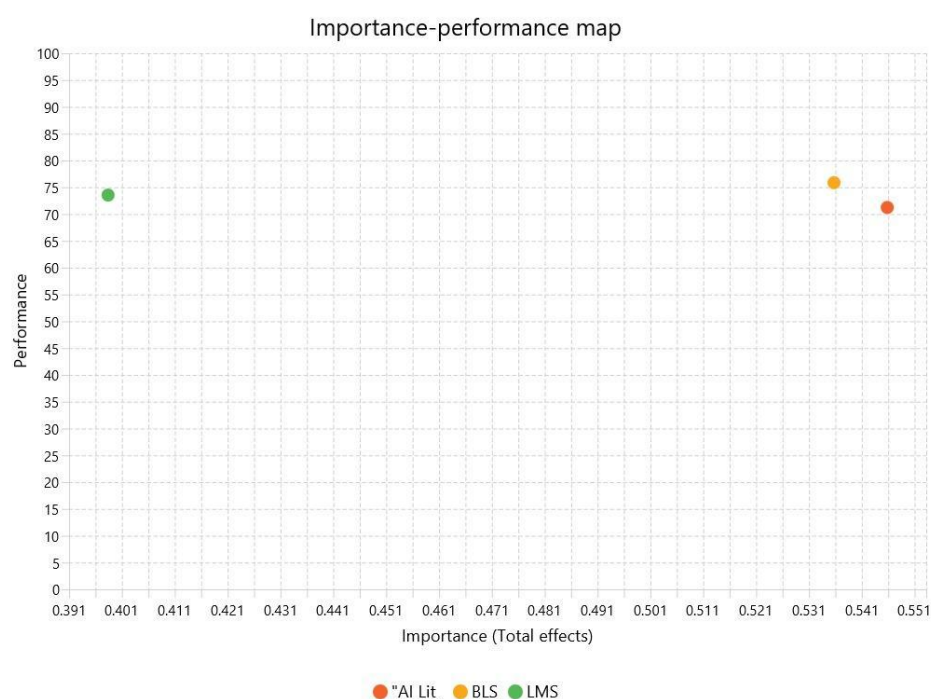


Figure 2. Importance-performance map showing the position of AI Literacy, BLS, and LMS

4. Discussion

Examining the potential roles of LMS quality and blended learning satisfaction explains the correlation between AI literacy and Academic performance among non-STEM students. The findings demonstrated well-established, straightforward pathways for AI literacy. Although both performance and AI literacy were related to the high-quality learning management system (LMS), the former affected the latter indirectly through user satisfaction. AI literacy becomes more important in the classroom when students can use a blended learning environment effectively.

4.1 H1: AI Literacy and Perceived LMS Quality

AI literacy is strengthened by its strong correlation with LMS quality beyond tool use. Interacting effectively with AI-enhanced technology is supported by its technological, cognitive, ethical, and practical characteristics (Hackl et al., 2026; Wang et al., 2023). Previous study showing a correlation between AI literacy and satisfaction with technology, these features could make learning management systems easier to navigate and make better use of available resources (Singh et al., 2024; Al-Abdullatif & Alsubaie, 2024)

4.2 H2: Perceived LMS Quality and Blended-Learning Satisfaction

The Information Systems Success Model (DeLone & McLean, 2003) posits that system quality precedes satisfaction and supports a positive correlation between LMS quality and blended learning satisfaction. These findings align with previous studies (Al-Fraihat et al., 2020; Alzahrani & Seth, 2021) suggesting a relationship between satisfaction and LMS functionality, accessibility, information and service quality. The extent to which the classroom fulfils

students' educational needs indicates satisfaction (Chen et al., 2023; Hassan et al., 2024; Panigrahi et al., 2024).

4.3 H3: Blended-Learning Satisfaction and Academic Performance

Blended learning satisfaction was strongly correlated with Academic performance, aligning with evidence that encouraging learning experiences support educational goals in a technology-mediated context. (Britwum et al., 2026). Students' satisfaction is unlikely to boost academic performance in a blended learning context. It may indicate a context where educational materials, technology, interaction, and feedback sustain engagement. The findings suggest that students' learning experiences are crucial to technology provision and academic values.

4.4 H4: LMS Quality and Academic Performance

The lack of a significant correlation between LMS quality and academic performance undermines the idea that greater digital infrastructure inherently increases accomplishment. LMS quality enables access, organisation, communication, and interaction, not results. This contrasts with studies linking system quality to performance benefits (Al-Fraihat et al., 2020). LMS quality may indirectly affect performance by shaping students' learning experiences.

4.5 H5: AI Literacy and Academic Performance

A positive correlation between AI literacy and academic performance supports the educational importance of AI-related abilities (Bećirović et al., 2025; Shi et al., 2025). Conflicting findings suggest that abilities may not ensure success (Bancoro, 2024; Widowati et al., 2023). AI literacy directly affects performance, but it's the learning environment also determines the benefits

4.6 H6: Mediating Role of LMS Quality

Positive impressions of the system do not automatically lead to better grades because of the insignificant indirect pathways through LMS quality. The educational importance of a learning management system (LMS) increases as it promotes fruitful learning experiences. Papers by Ai et al. (2026), Chen et al. (2023), and Minadzi and Segbenya (2024) support this view,

identifying enjoyment and engagement as mediating elements in technology-mediated learning.

4.7 H7: Sequential Mediation through LMS Quality and Blended-Learning Satisfaction

In terms of theoretical contribution, the sequential mediation results stands out. There was a correlation between AI literacy and LMS quality, which in turn was connected to blended learning satisfaction, academic performance, and LMS quality. System quality becomes academically consequential through satisfaction, as contrasted with the unsupported LMS only mediation and the supported sequential pathway. Integrating AI literacy as an prior learner abilities and showing that its academic values is relational rather than solely technical are two ways in which this discovery expands AI literate research and Information Systems Success Model (Hua et al., 2024; Kok et al., 2025)

5 Implications

5.1 Theoretical Implications

This study adds AI literacy was a distal predictor of individual sense of system quality to the Information Systems Success Models. The study also shows that learning management system (LMS) quality is not enough and that the quality satisfaction sequence provides a better explanation for performance. Thus, the model incorporates information system quality and AI use into a unified instructional process.

5.2 Practical Implications

The findings of the study shows that, technology-enabled learning can enhanced performance under certain conditions, such as instructor providing timely feedback, using well-structured materials, encouraging students communication, and providing support for students. A well-structured AI literacy program should accompany investments in system quality for learning management system administrators. This will ensure that students make a good use of the platform's feature. Policy makers should consider integrating AI literacy into non-STEM courses and ensuring fair access to digital infrastructure, as supported by the findings.

6 Limitations and Directions for Future Research

Some limitations apply to these findings include; Cross-sectional design cannot draw a casual conclusions; longitudinal or experimental designs are needed to demonstrate temporal ordering. One Ghanaian institution's non-STEM students limited generalisability; cross-disciplinary and cross-national replication is needed. All construct were self-reported, introducing usual technique bias. Future studies should triangulated against institutional data. Although all HTMT values were below .90, BLS↔AP and LMS↔AI Literacy had bootstrap upper bounds above.90, suggesting conceptual overlap requiring either item higher-order construct specification. Future studies could evaluate factors including prior AI exposure, gender, and academic year to see if STEM groups duplicate this mediation pathway.

7 Conclusion

AI literacy's contribution to non-STEM students' academic performance is primarily through a sequential mechanism, where perceived LMS quality shapes blended-learning satisfaction, which drives performance. These findings improve theory of technology-mediated learning and provide practical advice for instructors, administrators, and policymakers aiming to apply AI competency to non-STEM higher education in resource-constrained settings.

Data availability statement

Data available upon reasonable request, but restricted due to privacy/ethics.

CRedit authorship contribution statement

Charles Atta Koduah: Conceptualisation, Methodology, Data Curation, Data Collection, and Formal Analysis, Writing, Reviewing, and Editing. . **Harry Barton Essel:** Supervision, Composition - Initial Draft Development and Revision. **Prosper Setsoafia:** Methodology, Data Curation, Data Collection, and Formal Analysis. **Francis Kofi Nimo Nunoo:** Supervision, Original Draft Preparation, and Editing All authors have reviewed and endorsed the final manuscript. **Juliet Appiah-Kubi:** Conceptualisation, Methodology, Data Collection.

Akosua Tachie-Menson: Supervision, Original Draft Preparation, and Editing. **Edmund Boamah Acheampong:** Methodology, Data Collection. **George Atta Aboagye:** Methodology, Data Acquisition, Formal Analysis. **Machariuos Nabang:** Methodology, Data Curation, Data Collection.

Funding

This study received no external funding.

Declaration of competing interest

The authors declare no conflict of interest.

Acknowledgments

The authors express their gratitude to the individuals who dedicated their time to take part of this study.

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