

AI Literacy and Academic Performance: A Cross-Sectional Analysis of Senior High School Students

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Abstract

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This study investigates the relationship between artificial intelligence (AI) literacy and academic performance among senior high school students using the validated Artificial Intelligence Literacy Scale (AILS). A cross-sectional correlational study examined 525 students from four academic strands. Despite widespread AI tool adoption (85.7% use ChatGPT), learning remains predominantly informal and peer-driven rather than teacher-guided. AI literacy was measured across four dimensions: awareness, usage, evaluation, and ethics. Academic performance was assessed through grade point averages and standardized test scores. Results reveal significant positive relationships between AI literacy and academic performance ($r = .27-.28$, $p < .001$), with awareness and ethics dimensions emerging as primary predictors over technical usage skills. AI literacy explained 7.2% of variance in grades and 7.7% of variance in test scores. Students demonstrated significant variations across academic strands—STEM students significantly outperformed business and general academic students, while humanities students achieved levels comparable to STEM students. This suggests interdisciplinary approaches combining critical thinking with technology understanding may be optimal for AI literacy development. The prominence of conceptual understanding over technical skills challenges prevailing assumptions about AI education priorities. Findings provide empirical evidence for integrating strand-specific AI literacy curricula and demonstrate urgent need for systematic AI literacy education to address current informal learning gaps in secondary education globally.

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Introduction

The rapid integration of artificial intelligence (AI) across educational contexts necessitates developing AI literacy among students to prepare them for future academic and career challenges. AI literacy encompasses understanding AI technologies, applying them effectively, evaluating their capabilities, and recognizing ethical implications (Wang et al., 2022). As AI becomes increasingly pervasive in daily life and educational settings, understanding how AI literacy relates to academic performance has become crucial for educational policy and practice. The emergence of generative AI tools has further accelerated the need for comprehensive AI literacy education, with studies showing significant shifts in AI literacy research from primarily K-12 contexts to expanded post-secondary settings (Gu & Ericson, 2024).

AI literacy has emerged as a critical 21st-century competency, with various frameworks proposed to define its essential components. Ng et al. (2021) conducted an exploratory review identifying four aspects for fostering AI literacy: know and understand, use and apply, evaluate and create, and ethical issues. This framework builds upon classic literacy definitions while addressing AI-specific competencies, establishing groundwork for future research in competency development and assessment criteria. Building on this foundation, Wang et al. (2022) developed the Artificial Intelligence Literacy Scale (AILS), conceptualizing AI literacy through four constructs: awareness (ability to identify and comprehend AI technology), usage (ability to apply AI technology), evaluation (ability to analyze and critically evaluate AI applications), and ethics (awareness of responsibilities and risks). This framework has been validated across multiple contexts and provides a comprehensive approach to measuring AI competencies relevant to educational settings.

Recent systematic reviews have expanded understanding of AI literacy dimensions. Almatrafi et al. (2024) identified six key constructs through their review of 47 articles: Recognize, Know and Understand, Use and Apply, Evaluate, Create, and Navigate Ethically. Their findings have significant implications for future studies as they advance understanding of AI literacy implementations and assessment efforts across different disciplines. Zhou et al. (2025) emphasized the need to expand existing AI literacy definitions by including self-reflection and emotional aspects, particularly for K-12 education contexts. Their systematic review of 47 publications over ten years identified 13 topics to foster AI competency, five instructional designs, and five assessment approaches, highlighting that self-reflective mindsets were included in very few studies in AI education literature.

Research on AI literacy in K-12 education reveals diverse approaches and implementation challenges. Casal-Otero et al. (2023) conducted a systematic literature review of 179 documents, finding that learning experiences in schools have focused mainly on technical and applied skills limited to specific domains without rigorously assessing student learning outcomes. Their study revealed that the US and China are leading AI literacy implementation schemes which are broader in scope and involve more ambitious approaches. The challenges of implementing AI education in K-12 settings are multifaceted. Yim (2024) highlighted that AI literacy education mainly targets secondary and university students, often overlooking the unique needs of younger students. This gap in primary school AI literacy education presents theoretical and pedagogical challenges, particularly given the pervasive influence of AI and its potential to exacerbate inequalities.

The evolution of AI literacy education has been significantly impacted by generative AI. Gu and Ericson (2024) found that before generative AI, AI literacy was primarily studied in K-12 contexts where learners were introduced to both technical details of AI and AI ethics. Post-generative AI, research has significantly expanded to post-secondary contexts, emphasizing teaching effective use of generative AI tools such as prompt engineering. Hornberger et al. (2023) developed and validated an AI literacy test for university students, finding significant variance in AI literacy among students, with most showing fundamental understanding of AI. Their results indicated higher AI literacy among students with technical study backgrounds or prior AI experience, suggesting the need for effective AI courses for broader student audiences.

The relationship between technological literacy and academic performance has been extensively studied across educational levels. Lei et al. (2021) conducted a meta-analysis of 50 effect sizes from 45 studies involving 70,350 students, finding that students with greater ICT literacy often had substantially higher academic achievement. The positive link between ICT literacy and academic achievement was strongest among students in senior high school, followed by elementary school, junior high school, and lowest in university. Li et al. (2025) found significant medium-positive correlations ($r = 0.240$) between digital literacy and academic achievement in their meta-analysis of 35 independent effect sizes. Their results showed significant differences in correlation between digital literacy and academic achievement among students of different grade levels, orientations, subjects, sampling methods, and genders.

Mehrvarz et al. (2021) investigated the mediating role of digital informal learning between higher education students' digital competence and academic performance. Their study of 319 university students revealed that digital competence had a positive effect on students' academic performance, with digital informal learning serving as a mediating variable. Recent studies have also explored the relationship between AI literacy and other educational outcomes. Yaşar and Karagücük (2024) found statistically significant, moderate, and positive correlations between AI literacy and English language learning motivation, suggesting that students with higher AI literacy tend to exhibit greater motivation in language learning.

This study is grounded in two complementary theoretical perspectives. Technological Literacy Theory (Stolpe & Hallström, 2024) posits that technological literacy encompasses technical competencies, critical evaluation skills, and socio-ethical understanding, suggesting that students' ability to understand and critically evaluate AI technologies relates to their academic competence and problem-solving abilities. Cognitive Load Theory (Sweller, 1988) proposes that students with higher AI literacy may experience reduced cognitive load when encountering AI-enhanced learning environments, leading to better academic performance through more efficient information processing. Recent extensions incorporating AI and machine learning support this notion that technological competencies enhance cognitive processing efficiency (Gkintoni et al., 2025).

The conceptual framework posits direct relationships between AI literacy dimensions (awareness, usage, evaluation, and ethics) and academic performance measures (General Weighted Average and standardized test scores). Students with higher AI literacy are expected to demonstrate better academic outcomes through enhanced cognitive capabilities and technological fluency in AI-enhanced educational environments. Based on these

theoretical foundations, three hypotheses guide this investigation: (H1) there is a significant positive relationship between AI literacy and academic performance measures; (H2) AI literacy dimensions will significantly predict academic performance outcomes; and (H3) overall AI literacy will demonstrate significant predictive relationships with both internal and external academic assessments.

The Philippine context provides a unique setting for examining AI literacy and academic performance relationships. The K-12 educational system, implemented to align with international standards, creates diverse learning pathways through specialized academic strands. Recent research by Co (2025) supports the importance of considering these strand differences, demonstrating significant variations in how students across different academic strands evaluate technology-enhanced learning environments and faculty performance in digital education contexts, suggesting that academic specialization may fundamentally influence students' technology learning experiences. Additionally, the country's rapid digital transformation and increasing AI adoption in educational institutions necessitate understanding how students' AI competencies influence their academic success. Despite growing recognition of AI literacy's importance, empirical research examining its relationship with academic performance in secondary education remains limited, particularly in developing countries like the Philippines. While studies have explored AI literacy conceptualization (Ng et al., 2021; Almatrafi et al., 2024) and implementation efforts (Casal-Otero et al., 2023), few have investigated how AI literacy competencies relate to measurable academic outcomes among K-12 students.

This study addresses the empirical gap by investigating relationships between AI literacy and academic achievement among Filipino senior high school students in a technology-enhanced educational environment. The main objective is to examine the relationship between AI literacy dimensions and academic performance measures among SHS students, providing empirical evidence for AI literacy integration in the Philippine K-12 curriculum. The research questions guiding this investigation are:

- What is the relationship between AI literacy and academic performance among Filipino senior high school students?
- Which AI literacy dimensions best predict academic performance outcomes?
- How do AI literacy levels and academic performance vary across different academic strands?

Method

Research Design and Participants

This study employed a quantitative cross-sectional correlational design to examine relationships between AI literacy and academic performance among SHS students without manipulating variables. The cross-sectional approach was selected to provide a snapshot of the current state of AI literacy and its relationship with academic performance across different academic strands in the Philippine educational context.

The study included 525 SHS students from a private school in the Philippines with approximately 2,900 total SHS students. The sample comprised 320 Grade 11 students (61.0%) and 205 Grade 12 students (39.0%), representing a 20.3% response rate of the total SHS population. Participants were drawn from four academic strands: Science,

Technology, Engineering, and Mathematics (STEM, $n = 348$, 66.3%); Accountancy, Business, and Management (ABM, $n = 103$, 19.6%); Humanities and Social Sciences (HUMSS, $n = 46$, 8.8%); and General Academic Strand (GAS, $n = 28$, 5.3%).

The participating school provides a technology-rich learning environment that incorporates AI-enhanced educational platforms, creating a naturalistic context for examining AI literacy development. Students regularly interact with ALEKS (Assessment and Learning in Knowledge Spaces), an AI-powered adaptive learning platform for mathematics; Achieve3000, an AI-driven differentiated literacy platform; Canvas Learning Management System with AI-enhanced features; and receive explicit instruction on using generative AI tools for academic purposes with guidelines for ethical usage.

Data Collection and Instruments

Data were collected through an online survey administered to participants following school approval and ethical protocols. The survey instrument comprised two main sections: demographic information and the validated 12-item Artificial Intelligence Literacy Scale (AILS) developed by Wang et al. (2022). The AILS measures four dimensions of AI literacy—awareness, usage, evaluation, and ethics—using a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). The scale has demonstrated strong psychometric properties across multiple contexts, with reliability coefficients ranging from $\alpha = .82$ to $\alpha = .88$ across dimensions in the original validation study.

Academic performance data were obtained from official school records following established data privacy protocols. General Weighted Average (GWA) scores for participants' most recent completed semester were collected from the registrar's office. Standardized test scores were obtained differentially by grade level: Grade 11 students completed a Philippine standardized achievement test while Grade 12 students completed a Philippine college readiness assessment. These measures provided both internal (GWA) and external (standardized tests) perspectives on academic achievement.

Data Analysis

Data analysis was conducted using Jamovi statistical software (Version 2.3; The Jamovi Project, 2022), selected for its robust analytical capabilities and transparent reporting features appropriate for correlational research designs. Data cleaning procedures were implemented prior to analysis, beginning with an initial sample of 590 respondents. Cases were excluded based on the following criteria:

- (1) incomplete responses with missing data on key variables ($n = 45$),
- (2) response patterns indicating lack of engagement, specifically all responses marked as "1" (strongly disagree) across AILS items ($n = 12$), and
- (3) response patterns suggesting acquiescence bias with all responses marked as "7" (strongly agree) across AILS items ($n = 8$).

These exclusions resulted in a final analytical sample of 525 participants with complete and valid response patterns. Preliminary analyses included descriptive statistics, normality testing, and internal consistency reliability

evaluation using Cronbach's alpha for AILS dimensions in the current sample.

Primary analyses addressed the research questions through appropriate statistical techniques. Pearson correlations examined bivariate relationships between AI literacy dimensions and academic performance measures. One-way ANOVA with post-hoc tests examined differences in AI literacy and academic performance across academic strands. Multiple regression analyses identified unique predictive contributions of individual AI literacy dimensions while controlling for intercorrelations among predictors. Simple linear regression examined overall AI literacy as a predictor of academic performance. Statistical significance was set at $\alpha = .05$, with effect sizes interpreted according to Cohen's conventions.

Ethical Considerations

This study received school ethics approval and followed established protocols for educational research involving minors. Online surveys included embedded confidentiality statements, data privacy notices, and informed consent procedures, with participation entirely voluntary and anonymous. Academic performance data were obtained through official channels following school data privacy guidelines, with all data stored on password-protected systems accessible only to authorized research personnel.

Results

Participant Demographics, Technology Profile, and Reliability Analysis

The sample comprised 525 SHS students distributed across four academic strands: STEM (66.3%), ABM (19.6%), HUMSS (8.8%), and GAS (5.3%). Table 1 presents the comprehensive demographic and technology profile of participants, revealing a technologically engaged student population with high digital access and widespread AI tool adoption.

Nearly all participants (94.5%) have smartphone access, with substantial laptop ownership (73.7%) and reliable internet connectivity (88.6% home broadband). Most students demonstrate intensive digital engagement, with 41.5% using devices for schoolwork 5+ hours daily and 73.0% using devices for non-academic activities 5+ hours daily.

AI tool adoption is widespread among Filipino SHS students, with ChatGPT leading usage at 85.7%, followed by Google Assistant (66.7%) and Microsoft Copilot (61.0%). Regular AI usage is prevalent, with 57.1% using AI tools multiple times weekly and 19.2% using them daily. Notably, 81.3% of students have received some form of teacher instruction about AI tools, indicating school awareness and integration efforts. However, learning remains predominantly peer-driven and self-directed, with 37.5% self-teaching through online tutorials and 32.0% learning from peers, suggesting informal knowledge acquisition patterns that may contribute to variations in AI literacy development. The AILS demonstrated strong internal consistency in this sample, with Cronbach's alpha coefficients of $\alpha = .85$ for Awareness, $\alpha = .89$ for Usage, $\alpha = .88$ for Evaluation, and $\alpha = .84$ for Ethics, supporting the reliability of the instrument in the Philippine educational context.

Table 1. Demographic Profile and AI Technology Information of Respondents

Characteristic	Category	n	%
Grade Level	Grade 11	320	61.0
	Grade 12	205	39.0
Academic Strand	STEM	348	66.3
	ABM	103	19.6
	HUMSS	46	8.8
	GAS	28	5.3
Device Access	Smartphone	496	94.5
	Laptop/Desktop	387	73.7
	Tablet	312	59.4
Internet Connectivity	Home Broadband	465	88.6
	Mobile Data	478	91.0
	School WiFi	521	99.2
Daily Device Usage (Academic)	1-2 hours	89	17.0
	3-4 hours	218	41.5
	5+ hours	218	41.5
Daily Device Usage (Non-Academic)	1-2 hours	67	12.8
	3-4 hours	75	14.3
	5+ hours	383	73.0
AI Tool Usage	ChatGPT	450	85.7
	Google Assistant	350	66.7
	Microsoft Copilot	320	61.0
	Bard/Gemini	298	56.8
AI Usage Frequency	Daily	101	19.2
	Multiple times weekly	300	57.1
	Weekly	89	17.0
	Occasionally	35	6.7
AI Learning Sources	Teacher instruction	427	81.3
	Self-taught (online tutorials)	197	37.5
	Peer learning	168	32.0
	Workshop/training	89	17.0

AI Literacy and Academic Performance: Descriptive Statistics and Strand Differences

Students demonstrated moderately high AI literacy overall ($M = 5.39$, $SD = 0.82$ on a 7-point scale), with significant variations across academic strands. STEM students showed the highest overall AI literacy ($M = 5.45$, $SD = 0.78$), followed by HUMSS ($M = 5.44$, $SD = 0.91$), ABM ($M = 5.16$, $SD = 0.83$), and GAS ($M = 4.91$, $SD = 0.97$). One-way ANOVA revealed significant differences in overall AI literacy across strands, $F(3, 82.9) = 5.29$, $p = .002$. Post-hoc analyses using Tukey's HSD indicated that STEM students demonstrated significantly higher AI literacy than both ABM ($p = .011$) and GAS students ($p = .005$). Similarly, HUMSS students showed significantly higher AI literacy than GAS students ($p = .034$). Analysis of individual AI literacy dimensions revealed significant strand differences in awareness, $F(3, 81.2) = 6.17$, $p < .001$, and evaluation, $F(3, 82.3) = 3.62$,

$p = .016$. For awareness, STEM students scored significantly higher than ABM students ($p = .001$). For evaluation, both HUMSS ($p = .014$) and STEM students ($p = .003$) scored significantly higher than GAS students. No significant differences were found for usage, $F(3, 84.4) = 2.77$, $p = .047$, or ethics dimensions, $F(3, 85.5) = 1.38$, $p = .254$, after post-hoc corrections.

Table 2. Descriptive Statistics by Academic Strand

Variable	Strand	M	SD	n
AI Literacy Overall	ABM	5.16	0.83	103
	GAS	4.91	0.97	28
	HUMSS	5.44	0.91	46
	STEM	5.45	0.78	348
Awareness	ABM	5.23	1.03	103
	GAS	5.04	1.34	28
	HUMSS	5.50	1.12	46
	STEM	5.66	0.90	348
Usage	ABM	4.94	1.11	103
	GAS	4.77	1.12	28
	HUMSS	5.21	1.22	46
	STEM	5.22	1.08	348
Evaluation	ABM	5.20	1.16	103
	GAS	4.69	1.47	28
	HUMSS	5.51	1.22	46
	STEM	5.46	1.07	348
Ethics	ABM	5.28	1.05	103
	GAS	5.15	1.13	28
	HUMSS	5.56	1.04	46
	STEM	5.45	1.07	348
Grade Point Average	ABM	88.4	4.13	103
	GAS	85.4	4.17	28
	HUMSS	88.7	4.25	45
	STEM	89.0	3.05	348
Standardized Test Scores	ABM	295	32.9	103
	GAS	288	22.4	28
	HUMSS	307	26.0	46
	STEM	307	36.0	348

Academic performance also varied significantly across strands. GWA differences were significant, $F(3, 79.9) = 6.99$, $p < .001$, with ABM students showing higher GWA than GAS students ($p = .007$), and both HUMSS ($p = .009$) and STEM students ($p < .001$) outperforming GAS students. Standardized test scores showed similar patterns, $F(3, 95.4) = 7.69$, $p < .001$, with HUMSS and STEM students significantly outperforming ABM ($p = .007$) and GAS students ($p = .011$ and $p = .002$, respectively).

Correlational Analysis

Shown in table 3, significant positive correlations emerged between overall AI literacy and both academic performance measures (GWA: $r = .27, p < .001$; Standardized Test Scores: $r = .28, p < .001$).

Table 3. Correlation Matrix of Study Variables

Variable	1	2	3	4	5	6	7
1. Overall AI Literacy	--						
2. Awareness	.75***	--					
3. Usage	.81***	.50***	--				
4. Evaluation	.83***	.49***	.62***	--			
5. Ethics	.68***	.35***	.33***	.39***	--		
6. Grade Point Average	.27***	.25***	.17***	.18***	.22***	--	
7. Standardized Test Scores	.28***	.23***	.20***	.19***	.24***	.54***	--

Among individual dimensions, awareness and ethics showed the strongest correlations with academic performance measures, while usage and evaluation demonstrated weaker but significant relationships. All AI literacy dimensions showed strong positive intercorrelations (.33 to .83), supporting the multidimensional yet cohesive nature of AI literacy as a construct.

Predictive Relationships: Regression Analysis

Overall AI literacy significantly predicted both academic performance measures, explaining 7.2% of variance in GWA and 7.7% of variance in standardized test scores. When examining individual dimensions, awareness and ethics emerged as the primary predictors, while usage and evaluation showed no significant predictive value when controlling for other dimensions.

Table 4. Regression Results: AI Literacy Predicting Academic Performance

Predictor	Grade Point Average			Standardized Test Scores		
	β	t	p	β	t	p
Model 1: Overall AI Literacy						
AI Literacy Overall	.268	6.35	<.001	.278	6.62	<.001
R ²	.072			.077		
F	40.3***			43.9***		
Model 2: Individual Dimensions						
Awareness	.183	3.58	<.001	.120	2.36	.019
Usage	.014	0.26	.798	.070	1.24	.215
Evaluation	.029	0.51	.608	.027	0.47	.638
Ethics	.141	3.02	.003	.163	3.49	<.001
R ²	.085			.085		
F	12.1***			12.1***		

Awareness demonstrated the strongest predictive power for GWA ($\beta = .183$, $p < .001$) and significant prediction for standardized tests ($\beta = .120$, $p = .019$). Ethics showed consistent predictive value across both performance measures ($\beta = .141$ for GWA, $\beta = .163$ for standardized tests, both $p < .01$), indicating that understanding AI-related responsibilities and risks contributes to academic success.

Discussion

Technology Landscape and Informal Learning Patterns

The extensive technology adoption among Filipino SHS students (94.5% smartphone access, 85.7% ChatGPT usage) provides important context for understanding AI literacy development, reflecting broader patterns observed in digital literacy research where students demonstrate high technological engagement (Maria et al., 2024). The prevalence of informal learning approaches—with 37.5% self-teaching and 32.0% peer learning despite 81.3% receiving teacher instruction—suggests that current educational frameworks may be insufficient to meet students' AI learning needs. This gap between formal instruction and informal acquisition may contribute to the observed variations in AI literacy across strands, as students with different academic orientations may have varying access to peer networks and self-directed learning resources.

These patterns align with Su et al. (2023) who identified challenges in AI literacy implementation including lack of teachers' AI knowledge and curriculum design. The intensive daily device usage (5+ hours for both academic and non-academic purposes) indicates that today's Filipino students are digital natives who naturally integrate technology into their daily routines, making AI literacy development a natural extension of their existing technological engagement rather than an entirely new competency domain.

Differential Predictive Power of AI Literacy Dimensions

The prominence of awareness and ethics dimensions as primary predictors, while usage and evaluation showed limited unique predictive value, provides important insights for educational practice. This finding suggests that understanding AI concepts and ethical implications may be more crucial for academic success than practical application skills or critical evaluation abilities. This aligns with Ng et al. (2021) and Casal-Otero et al. (2023), who emphasize that learners should understand underlying AI concepts and ethical concerns rather than merely knowing how to use AI applications.

This pattern is further supported by Zhou et al. (2025) who identified the need to expand existing AI literacy definitions by including self-reflection and emotional aspects, particularly emphasizing conceptual understanding over technical skills. The stronger predictive power of awareness supports Technological Literacy Theory's emphasis on conceptual understanding as a foundation for technological competence, as validated by Masdoki et al. (2024) who found that technological literacy has a positive relationship with educator competencies. Students who can recognize and understand AI technologies may be better equipped to leverage these tools effectively across academic tasks, leading to improved performance. Similarly, the predictive power of ethics aligns with frameworks emphasizing the importance of responsible technology use and critical thinking about technology's

societal implications (Chiu et al., 2024; Gouseti et al., 2024).

Strand-Specific Implications for Curriculum Design

The significant variations in AI literacy across academic strands have important implications for curriculum design and pedagogical approaches. The lower AI literacy levels among GAS students, who showed the poorest performance across most dimensions, suggest the need for targeted interventions to ensure equitable AI literacy development across all academic pathways. The strong performance of HUMSS students in AI literacy, particularly in awareness and evaluation dimensions, suggests that combining technological education with humanities-based critical thinking may be particularly effective for developing comprehensive AI competencies. This finding supports calls for interdisciplinary approaches to AI literacy education that go beyond technical training to include ethical reasoning and critical evaluation skills, as advocated by Casal-Otero et al. (2023) who argue for competency-based approaches integrated into school curricula rather than standalone AI subjects.

For STEM students, who already demonstrate high AI literacy levels, educational efforts might focus on advanced applications and deeper technical understanding. For ABM students, integrating AI literacy with business and management contexts could enhance both technological competence and domain-specific applications. This differentiated approach aligns with Gorospe and Joaquin (2022) who found that academic strand influences students' preparation for higher education, though they noted that the strand is becoming less of a factor in college program selection.

Educational Implications for Philippine K-12 System

These findings have specific relevance for the Philippine K-12 educational system. The study provides baseline data for AI literacy among Filipino SHS students across different academic strands, informing policy development and curriculum design efforts. The moderate AI literacy levels ($M = 5.39/7.0$) with significant strand variations suggest both opportunities for improvement and the need for differentiated approaches, consistent with ongoing evaluations of the K-12 system's effectiveness (Almerino et al., 2020).

The consistent relationships between AI literacy and both internal (GWA) and external (standardized test) assessments indicate that AI literacy contributes to general academic competence rather than specific test-taking skills. This finding supports the integration of AI literacy development across academic disciplines and strands rather than as isolated technical training, aligning with Jadaone et al. (2022) who found that blended learning environments can enhance students' preparation for higher education when properly implemented.

The practical significance of AI literacy effects, while statistically significant, is modest (7-8% variance explained). However, these effect sizes are meaningful in educational contexts where multiple factors influence academic performance, as demonstrated by Sopandi et al. (2022) who found similar moderate but significant relationships between digital capabilities and student performance in Indonesian Islamic schools. The improvements in academic outcomes could influence students' educational trajectories and future opportunities,

particularly important in the Philippine context where academic performance significantly affects college admission and career prospects.

Theoretical Contributions and Support

This research contributes to theoretical understanding by providing empirical validation of the AILS framework in a secondary education context across different academic specializations. The strong internal consistency reliability across all dimensions ($\alpha = .84-.89$) and meaningful relationships with academic outcomes support the construct validity of the four-dimensional AI literacy model in diverse K-12 settings, consistent with validation studies by Çelebi et al. (2023) and Uğraş et al. (2024) in different cultural contexts. The findings support Technological Literacy Theory by demonstrating that technological competencies (AI literacy) relate to academic performance through enhanced problem-solving capabilities and critical thinking skills, with the prominence of awareness and ethics dimensions particularly supporting the theory's emphasis on both technical competencies and socio-ethical understanding as foundations for technological literacy.

The research also provides evidence for Cognitive Load Theory applications in AI-enhanced learning environments, where students with higher AI literacy, particularly in awareness and ethics dimensions, may experience reduced cognitive load when encountering AI tools and AI-enhanced educational content, leading to better academic performance through more efficient information processing and more thoughtful technology use. This aligns with recent extensions of Cognitive Load Theory that incorporate AI and machine learning contexts (Gkintoni et al., 2025; Vasilaki & Mavrogianni, 2025), supporting the notion that technological competencies enhance cognitive processing efficiency in educational settings.

Conclusion

This study provides valuable empirical evidence for the relationship between AI literacy and academic performance among Filipino senior high school students across different academic strands. The findings demonstrate that students with higher AI literacy tend to achieve better academic outcomes, with awareness and ethics dimensions being particularly important predictors. Significant variations in AI literacy across academic strands highlight the need for differentiated approaches to AI literacy education, with STEM students showing the highest levels and GAS students requiring additional support.

Several limitations should be considered when interpreting these findings. The cross-sectional design limits causal inferences about the relationship between AI literacy and academic performance, while longitudinal research is needed to establish causal relationships and examine AI literacy development over time across different academic strands. The single private school setting may limit generalizability to other educational contexts, particularly public schools with different resource levels and technological infrastructure, though the participating school's technology-rich environment provides insight into potential outcomes when AI tools are systematically integrated into education. The uneven distribution across academic strands limited some statistical analyses and may affect the representativeness of findings for smaller strands, suggesting future research should ensure more balanced

sampling across strands to enable robust comparative analyses.

Recommendations

Based on these findings, the study recommends educational stakeholders to integrate AI literacy across academic strands with differentiated approaches considering strand-specific contexts, emphasize awareness and ethics dimensions alongside technical skills particularly for underperforming strands, and develop interdisciplinary approaches combining AI education with humanities, business, and sciences perspectives. Systematic teacher training programs should focus on AI literacy instruction across strands with professional development emphasizing awareness and ethics dimensions, while policymakers should establish national AI literacy standards specifying competencies for different strands and grade levels, prioritize funding for AI literacy programs especially in under-resourced schools, and create assessment frameworks monitoring AI literacy development across diverse contexts. Future research should conduct longitudinal investigations establishing causal relationships across strands, expand to diverse educational contexts including public schools, examine targeted intervention programs for underperforming strands, and develop culturally responsive AI literacy frameworks suitable for the Philippine context and similar developing nations.

Statements and Declarations

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Ethical Considerations: This study obtained school ethics approval and adhered to established protocols for educational research with minors. Participants were informed of their voluntary participation rights, withdrawal options, and that their responses would be used exclusively for research while maintaining complete anonymity.

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