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AI Literacy and Self-Regulated Learning as Drivers of Academic Readiness

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ABSTRACT

This study investigated how AI literacy and self-regulated learning contributed to the academic readiness of secondary learners in Roxas, Isabela. Using an explanatory-predictive cross-sectional design, data were gathered from 222 Grade 8 learners selected through probability-proportional-to-size systematic sampling. AI literacy, self-regulated learning, and academic readiness were assessed using validated instruments, while Partial Least Squares Structural Equation Modeling, PLSpredict, and importance-performance map analysis were employed to test explanatory and predictive relationships. Results showed moderate levels of AI literacy, self-regulated learning, and academic readiness. Learners demonstrated stronger information-seeking and technology-use behaviors but showed weaker performance in time management, self-evaluation, AI evaluation, and ethical use. Both AI literacy and self-regulated learning significantly predicted academic readiness, with self-regulated learning emerging as the stronger driver. The model explained 56.3% of the variance in academic readiness and demonstrated moderate out-of-sample predictive power. Importance-performance analysis further identified time management and planning, AI evaluation, and ethical judgment as priority areas for learner support. The findings indicate that readiness for technology-supported learning depends not only on familiarity with AI tools but also on learners' capacity to regulate their learning and critically assess AI-generated information. Schools are therefore encouraged to integrate AI literacy development with structured self-regulation activities that strengthen independent, responsible, and reflective learning.

Keywords: *academic readiness; AI literacy; Artificial intelligence; secondary learners; self-regulated learning; technology-supported learning*

INTRODUCTION

Artificial intelligence has become increasingly present in the academic work of secondary learners through search tools, writing applications, adaptive platforms, automated feedback systems, and generative AI. Access to these tools, however, does not necessarily mean that learners understand how artificial intelligence works or how its outputs should be judged. AI literacy involves the ability to recognize AI, understand its basic functions, interact with it effectively, and critically evaluate its capabilities and limitations (Long & Magerko, 2020). This form of literacy becomes particularly important when students use AI for school tasks because the quality of learning depends not only on obtaining information but also on knowing when that information is accurate, appropriate, and ethically used. Ng et al. (2021) further described AI literacy through competencies involving understanding, application, evaluation, creation, and ethical awareness, suggesting that meaningful AI use requires judgment rather than simple technical familiarity.

The growing independence expected from learners in technology-supported instruction also places greater value on self-regulated learning. Students are often required to manage deadlines, select appropriate resources, monitor their understanding, sustain effort, and adjust their learning strategies with less immediate teacher direction. Self-regulated learning brings these processes together by explaining how learners manage cognition, motivation, behavior, and reflection while pursuing academic goals (Panadero, 2017). Its importance is especially visible in digitally mediated learning, where students have greater control over what they access and how they complete learning activities. Evidence from secondary education showed that learners demonstrating stronger patterns of online self-regulated activity also tended to achieve better learning outcomes than those showing limited engagement in these processes (van Alten et al., 2021).

AI literacy and self-regulated learning may therefore represent two complementary capacities needed for academic readiness. A learner may know how to operate AI tools yet still struggle to plan, monitor, and evaluate learning. In the same way, a highly self-directed learner may encounter difficulty when required to assess AI-generated information, recognize its limitations, or use it responsibly. Research on AI literacy education in secondary schools has shown that effective preparation includes not only technical knowledge but also evaluation, communication, collaboration, and ethical use of AI for further study and future work (Ng et al., 2024). At the policy level, educational use of generative AI has also been linked with the need to preserve human agency, critical judgment, and appropriate pedagogical use rather than allowing technology to replace meaningful learning processes (Miao & Holmes, 2023).

These concerns provide a basis for examining how AI literacy and self-regulated learning work together as drivers of academic readiness among secondary learners. While each construct has received considerable scholarly attention, understanding their combined contribution can offer a more useful picture of whether students are prepared to learn effectively in technology-supported environments. For secondary education in Roxas, Isabela, such evidence can help clarify whether learners possess both the competence to engage critically with AI and the capacity to manage their own learning. Thus, the study AI Literacy and Self Regulated Learning as Drivers of Academic Readiness seeks to determine how these two learner capacities contribute to readiness for academic demands shaped by increasingly technology-supported instruction.

Literature Review

AI Literacy as a Multidimensional Learner Competence

AI literacy extends beyond knowing how to operate artificial intelligence applications. Among secondary learners, it involves knowledge of AI concepts, the ability to reason about how AI functions, and an awareness of its personal and social implications. Zhong and Liu (2025) developed and validated an AI literacy framework specifically for secondary students and identified three broad dimensions: AI knowledge, AI affectivity, and AI thinking. Their findings indicate that meaningful AI competence combines conceptual understanding with higher-order reasoning and attitudes toward human and societal uses of AI. A related measurement study by Carolus et al. (2023) identified competencies involving the understanding, detection, application, and ethical use of AI, together with self-efficacy and self-management. These findings suggest that evaluating AI literacy among learners should account for both technical understanding and the judgment needed to use AI responsibly in academic tasks.

Self-Regulated Learning in Technology-Supported Instruction

Technology-supported learning gives students greater access to resources, but it also requires them to make more decisions about how they learn. Effective self-regulation involves setting learning goals, choosing strategies, monitoring progress, and reflecting on outcomes. Heikkinen et al. (2023), in a systematic review of learning analytics interventions, found that technology can support different phases of self-regulated learning, although interventions are more effective when planning, performance, and reflection are addressed together. Chiu (2024) likewise explained that generative AI can support self-regulated learning by assisting students with

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activities related to motivation, task performance, and reflection. These studies indicate that technology becomes academically useful when learners maintain control over their goals and decisions rather than depending on automated support to direct the entire learning process.

Academic Readiness for Technology-Supported Learning

Academic readiness in digitally supported education involves more than access to devices or familiarity with online platforms. Vo et al. (2024), in their validation study involving secondary students, identified technology readiness, learner control, online communication self-efficacy, self-directed learning, and learning motivation as important components of readiness. They also found that purposeful familiarity with digital activities, such as accessing learning materials and educational videos, was positively associated with students' readiness for online learning. Similarly, Cheon et al. (2021) demonstrated that readiness includes several interconnected learner capacities and can be examined to identify areas where students may require additional support. These findings position academic readiness as a combination of technological capability, confidence, motivation, and the capacity to direct one's own learning.

Linking AI Use, Self-Regulation, and Academic Readiness

The educational value of AI depends partly on whether learners can integrate its assistance into purposeful learning behaviors. Guan et al. (2025) found that educational chatbots can support learners in locating resources, applying learning strategies, and monitoring their understanding, although support for goal setting, planning, and reflection remains less developed. This limitation reinforces the need for learners to exercise their own regulatory skills while interacting with intelligent tools. Xia et al. (2026) further identified several ways generative AI can support self-regulated learning, including personalized goal development, resource analysis, progress monitoring, strategy selection, feedback, and self-assessment. Taken together, these findings support the view that AI literacy and self-regulated learning can operate as complementary capacities. Learners who can critically use AI while planning, monitoring, and evaluating their learning may be better prepared to meet academic demands in technology-supported secondary education.

METHODS

Research Design

The study employed an explanatory-predictive cross-sectional design using latent-variable modeling. Rather than limiting the analysis to conventional correlations, the design examined how AI literacy and self-regulated learning explained and predicted academic readiness for technology-supported learning. The explanatory component estimated the strength and direction of the structural relationships, while the predictive component assessed whether the model could generate useful predictions beyond the observed sample. This approach was consistent with the use of Partial Least Squares Structural Equation Modeling when prediction and explanation were considered jointly in educational research (Hair & Alamer, 2022).

Research Locale

The study was conducted in Roxas, Isabela, within the secondary education setting. The municipality provided an appropriate setting because learners experienced academic activities involving digital resources, internet-based materials, electronic communication, and other technology-supported learning practices. The locale therefore allowed AI literacy, learning regulation, and academic readiness to be examined within learners' regular educational experiences.

Participants and Sampling Technique

The participants were 222 Grade 8 learners enrolled in secondary education in Roxas, Isabela. The sample of 222 was obtained using Cochran's finite-population procedure at a 95% confidence level and 6% precision.

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of Education, Research, and Innovation Perspectives
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Probability-proportional-to-size systematic sampling was then applied so that learners from larger and smaller enrollment groups were represented according to their share of the population. No school names were retained in the research database.

Research Instrument

Data were gathered through a structured questionnaire composed of three validated measures. AI literacy was measured using the 12-item Artificial Intelligence Literacy Scale of Wang et al. (2023), covering awareness, use, evaluation, and ethics. The original validation reported an overall Cronbach's alpha of .83, with dimension coefficients of .73, .75, .78, and .73, respectively. Self-regulated learning was measured using the Self-Regulated Learning Questionnaire developed for secondary students by Öz and Şen (2018). Its 39 items represented studying method, self-evaluation, receiving support, time management and planning, and information seeking, with a reported overall Cronbach's alpha of .94 and a supported five-factor structure. Academic readiness for technology-supported learning was assessed through the 16-item Online Learning Readiness Scale for High School Students of Ramazanoğlu et al. (2022). Its computer self-efficacy, internet self-efficacy, and self-learning dimensions produced Cronbach's alpha coefficients of .83, .82, and .84, respectively. Confirmatory analysis also supported its structure, with CFI = .963, TLI = .956, and SRMR = .052.

The assembled questionnaire was subjected to language and content review before administration. A separate pilot administration involving 30 Grade 8 learners who were not part of the main sampling frame was designated to examine clarity, response time, and local internal consistency.

Data Gathering

Permission to conduct the study was secured from the appropriate educational authorities before data collection. Because the participants were minors, parental or guardian consent and learner assent were obtained before questionnaire administration. The selected learners received standardized instructions explaining the purpose of the study, the voluntary nature of participation, and the absence of academic consequences for declining or withdrawing. Questionnaires were administered during an agreed period without collecting learners' names. Completed responses were checked for missing data and patterned responding before encoding. Each valid questionnaire was assigned a numerical code, and the cleaned dataset was prepared for statistical analysis.

Data Analysis

The analysis used Partial Least Squares Structural Equation Modeling with PLSpredict, an approach suited to examining both explanatory relationships and predictive performance (Shmueli et al., 2019). Means and standard deviations were first computed to describe AI literacy, self-regulated learning, and academic readiness without producing respondent profile analyses. The measurement model was assessed through indicator loadings, composite reliability, rho_A, average variance extracted, and the heterotrait-monotrait ratio. The structural model then examined collinearity, standardized path coefficients, coefficient of determination, effect size, and predictive relevance. Statistical significance was established through 10,000 bootstrap resamples. In addition, PLSpredict with 10-fold cross-validation was used to determine out-of-sample predictive performance by examining Q^2_predict and prediction errors against a linear benchmark. An importance-performance map analysis was subsequently employed to identify which dimensions of AI literacy and self-regulated learning offered the strongest practical leverage for improving academic readiness. This combination provided more information than ordinary correlation or multiple regression because it evaluated explanation, prediction, and practical importance within the same model.

Ethical Considerations

The study observed voluntary participation, informed parental consent, learner assent, confidentiality, and the right to withdraw without penalty. No personally identifying information was included in the analytical dataset, and collected records were used solely for research purposes. Access to the data was restricted to authorized research work, and results were presented only in aggregated form to prevent identification of individual learners or participating institutions.

RESULTS AND DISCUSSION

Table 1. *Descriptive Results for the Major Study Variables*

Construct/Dimension	Mean	SD	Interpretation
AI Literacy	3.11	0.62	Moderate
Awareness	3.37	0.66	Moderate
Use	3.26	0.68	Moderate
Evaluation	2.91	0.71	Moderate
Ethics	2.88	0.73	Moderate
Self-Regulated Learning	3.29	0.59	Moderate
Studying method	3.38	0.65	Moderate
Self-evaluation	3.17	0.67	Moderate
Receiving support	3.44	0.63	Moderate
Time management and planning	2.96	0.72	Moderate
Information seeking	3.50	0.61	High
Academic Readiness	3.24	0.61	Moderate
Computer self-efficacy	3.31	0.66	Moderate
Internet self-efficacy	3.47	0.64	Moderate
Self-learning	2.93	0.70	Moderate

Scale: 1.00–1.80 = Very Low; 1.81–2.60 = Low; 2.61–3.40 = Moderate; 3.41–4.20 = High; 4.21–5.00 = Very High.

Table 1 presents a generally moderate level of AI literacy, self-regulated learning, and academic readiness among the secondary learners. The finding indicates that the learners possessed workable competencies but had not yet developed them to a consistently strong level. AI literacy obtained a mean of 3.11, with evaluation and ethics emerging as its weakest components. Learners therefore appeared more comfortable recognizing and using AI than judging the reliability, limitations, and responsible use of its outputs. This distinction is important because functional access to AI does not automatically produce critical or responsible use.

Self-regulated learning registered the highest overall mean at 3.29. Information seeking was relatively strong, but time management and planning recorded only 2.96. The pattern suggests that learners were willing to search for information and assistance but experienced greater difficulty organizing learning activities independently. Academic readiness was likewise moderate, with self-learning obtaining the lowest mean of 2.93. Thus, learners appeared more confident in accessing technology than in managing learning without continuous external direction. This finding reveals the central problem of the study: technological familiarity was developing faster than the learner capacities required for independent and critical academic work.

Table 2. *Reliability and Convergent Validity of the Measurement Model*

Construct	Loading Range	Cronbach's α	rho_A	Composite Reliability	AVE
AI Literacy	.684–.842	.874	.881	.899	.529
Self-Regulated Learning	.672–.866	.928	.934	.939	.506
Academic Readiness	.701–.884	.892	.899	.916	.576

Table 2 presents the measurement properties of the three latent constructs. Indicator loadings ranged from .672 to .884, while composite reliability values ranged from .899 to .939. Cronbach's alpha and rho_A coefficients were also above .80 for all constructs. The average variance extracted ranged from .506 to .576, indicating that each latent construct explained more than half of the variance of its indicators.

Although several indicators had loadings slightly below .708, they were retained because their removal did not materially improve composite reliability or AVE and because they represented meaningful dimensions of the constructs. The overall results supported satisfactory internal consistency and convergent validity. This established an adequate measurement foundation before examining the structural relationships among AI literacy, self-regulated learning, and academic readiness, consistent with recommended PLS-SEM evaluation procedures (Hair & Alamer, 2022).

Table 3. *Heterotrait-Monotrait Ratio of Correlations*

Construct	AI Literacy	Self-Regulated Learning	Academic Readiness
AI Literacy	1.000		
Self-Regulated Learning	.642	1.000	
Academic Readiness	.707	.811	1.000

Table 3 presents the HTMT values used to determine whether the constructs remained empirically distinct. Values ranged from .642 to .811, with none exceeding the conservative .85 criterion. The highest association occurred between self-regulated learning and academic readiness at .811. This was theoretically reasonable because readiness for independent academic work requires many of the planning, monitoring, and persistence behaviors represented by self-regulation.

The results nevertheless showed that the constructs were not statistical duplicates. AI literacy represented competence in dealing with artificial intelligence, self-regulated learning captured learner management of the learning process, while academic readiness represented preparedness to function successfully under technology-supported academic demands. Establishing these distinctions was particularly important because strong correlations without discriminant validity could have weakened the interpretation of the structural paths.

Table 4. *Structural Model Results for Academic Readiness*

Structural Path	β	SE	t-value	p-value	95% CI	f^2	Decision
AI Literacy → Academic Readiness	.287	.061	4.705	<.001	[.168, .404]	.114	Significant
Self-Regulated Learning → Academic Readiness	.521	.058	8.983	<.001	[.408, .632]	.377	Significant

Model statistics: R^2 = .563; Adjusted R^2 = .559; Q^2 = .319; maximum inner VIF = 1.46.

Table 4 presents the principal structural findings of the study. Both AI literacy and self-regulated learning significantly predicted academic readiness. AI literacy produced a positive effect of $\beta = .287$, $p < .001$, demonstrating that learners who were better able to understand, use, and assess AI also tended to demonstrate greater readiness for technology-supported academic work.

Self-regulated learning emerged as the stronger driver of academic readiness, with $\beta = .521$, $p < .001$. Its effect size of .377 was substantially larger than the .114 effect associated with AI literacy. This result suggests that knowing how to engage with AI was important, but learners' capacity to plan, monitor, adjust, and sustain their own learning contributed more strongly to readiness. AI therefore appeared to function most productively when learners already exercised meaningful control over their academic behavior.

Together, AI literacy and self-regulated learning explained 56.3% of the variance in academic readiness, indicating substantial explanatory value for a learner-centered educational model. The Q^2 value of .319 further indicated predictive relevance, while the maximum VIF of 1.46 showed no problematic collinearity. The findings therefore supported the central proposition of the study that academic readiness was driven not simply by

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technology competence but by the combination of critical AI capability and disciplined learner regulation. Studies involving secondary students have likewise emphasized that access to generative AI must be accompanied by critical judgment, learning control, and appropriate educational guidance because familiarity alone may encourage dependence rather than meaningful learning (Hsieh et al., 2026).

Table 5. *PLSpredict Results for Academic Readiness*

Academic Readiness Indicator	Q^2_predict	PLS-SEM RMSE	Linear Model RMSE	PLS Prediction
Computer self-efficacy	.318	.603	.629	Better
Internet self-efficacy	.284	.638	.631	Slightly weaker
Self-learning	.367	.587	.614	Better

Table 5 presents the out-of-sample predictive assessment using 10-fold PLSpredict. All Q^2_predict values were greater than zero, demonstrating that the model predicted unseen observations better than a naïve benchmark. PLS-SEM also generated lower prediction errors than the linear model for computer self-efficacy and self-learning. The error for internet self-efficacy was slightly higher than that produced by the linear benchmark.

The pattern indicated moderate predictive power rather than perfect prediction. This result added realism to the model because academic readiness was not completely determined by AI literacy and self-regulation. Other influences, such as instructional support, quality of connectivity, access to devices, learning environment, teacher guidance, and previous academic experiences, could contribute to readiness but were outside the specified model. The result also supported the use of predictive assessment because explanatory strength alone does not establish whether a structural model will perform well with observations outside the estimation sample (Shmueli et al., 2019).

Table 6. *Importance-Performance Map Analysis*

Predictor/Dimension	Importance for Academic Readiness	Performance Index	Priority
Self-Regulated Learning	.521	57.3	High
Time management and planning	.162	49.0	Very High
Self-evaluation	.116	54.3	High
Studying method	.098	59.5	Moderate
Information seeking	.074	62.5	Moderate
Receiving support	.071	61.0	Moderate
AI Literacy	.287	52.8	High
AI evaluation	.101	47.8	Very High
AI use	.074	56.5	Moderate
AI awareness	.061	59.3	Moderate
AI ethics	.051	47.0	High

Performance indices were expressed on a 0–100 scale.

Table 6 presents the importance-performance analysis and provides the most practical finding of the study. Self-regulated learning showed the greatest total importance for academic readiness, yet its performance remained only 57.3. Within this construct, time management and planning emerged as the clearest intervention priority, recording the highest dimension-level importance at .162 but a low performance score of 49.0. Improving this area therefore offered greater potential for strengthening academic readiness than simply increasing learners' exposure to technology.

A similar concern appeared within AI literacy. AI evaluation obtained an importance score of .101 but a performance value of only 47.8. Learners therefore required stronger preparation in determining whether AI-generated information was accurate, relevant, sufficiently supported, biased, or appropriate for a particular academic task. AI ethics also showed low performance at 47.0. These results suggest that programs centered only on teaching students how to access or prompt AI tools would address the less urgent side of the problem. The stronger need involved developing judgment about AI outputs and ensuring that learners retained responsibility for their own thinking.

Taken together, the IPMA results refined the structural findings. Self-regulated learning was the stronger overall driver, while specific weaknesses in time management, self-evaluation, AI evaluation, and ethical judgment represented areas where learner development had not kept pace with technology use. This pattern supports emerging evidence that AI literacy encompasses technical, personal, and critical competencies and that weaknesses in critical evaluation and responsible use can limit the educational benefit of generative AI (Reicho et al., 2026).

CONCLUSION

AI literacy and self-regulated learning both contributed significantly to the academic readiness of secondary learners, with self-regulated learning emerging as the stronger predictor. Although learners showed workable competence in using technology and seeking information, weaknesses remained in time management, self-evaluation, critical assessment of AI-generated content, and ethical AI use. These findings indicate that academic readiness depends not only on access to digital tools but also on the learner's ability to manage learning independently and make sound judgments when using artificial intelligence. It is therefore recommended that schools strengthen learning programs that integrate AI literacy with self-regulation activities, particularly through structured study planning, reflective learning tasks, verification of AI-generated information, ethical-use guidelines, and opportunities for learners to evaluate the reliability and appropriateness of AI outputs. Teachers may also incorporate guided AI-supported activities that require students to justify, revise, or reject generated responses rather than accept them automatically. Future research may extend the model by examining other factors that could influence academic readiness, such as teacher support, digital access, academic motivation, and quality of technology-supported instruction.

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Volume 2 Issue 9 (September 2026)

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