Self-Regulated Learning as a Mediator between AI Literacy, Academic Resilience, and Academic Performance among University Students

Minarni[1], Muhammad Yaumi[2], Ulfiani Rahman[3], Chairati Saleh[4]

[1]Universitas Bosowa, Makassar, Indonesia
[2]Universitas Islam Negeri Alauddin Makassar, Makassar, Indonesia
[3]Universitas Islam Negeri Alauddin Makassar, Makassar, Indonesia
[4]Universitas Islam Negeri Alauddin Makassar, Makassar, Indonesia

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ABSTRACT:
The rapid integration of artificial intelligence (AI) technologies into higher education has transformed how students learn, access information, and engage in academic activities. However, limited research has examined the psychological mechanisms through which AI literacy contributes to academic performance. This study investigates the relationships among AI literacy, academic resilience, self-regulated learning (SRL), and academic performance among university students, with SRL examined as a mediating variable. Using a quantitative cross-sectional design, data were collected from 760 university students in Indonesia through structured questionnaires. Structural Equation Modeling (SEM) was employed to analyze both direct and indirect relationships among the study variables. The findings revealed that AI literacy and academic resilience positively predicted both self-regulated learning and academic performance. Self-regulated learning also significantly predicted academic performance and partially mediated the relationships between AI literacy, academic resilience, and academic performance. The structural model demonstrated excellent goodness-of-fit indices ($\chi^2/df = 1.44$, RMSEA = 0.024, CFI = 0.99, TLI = 0.99, SRMR = 0.043). The study contributes to educational psychology literature by integrating technological competence and psychological resilience within a unified self-regulated learning framework in AI-supported higher education contexts. The findings also provide practical implications for universities seeking to enhance students' adaptive learning competencies and academic success in increasingly digital learning environments.

Keywords: Academic performance; Academic resilience; AI literacy; Self-regulated learning; Structural equation modeling

1. Introduction

The rapid advancement of artificial intelligence (AI) has substantially transformed the landscape of higher education worldwide (Vieriu & Petrea, 2025; Chan & Wu, 2023). The emergence of generative AI technologies, such as ChatGPT and other AI-assisted learning systems, has altered how students access information, complete academic tasks, and engage in

independent learning activities (Kim et al., 2024). Recent developments in AI-integrated education have encouraged universities to reconsider traditional pedagogical approaches and adapt to technology-enhanced learning environments that emphasize autonomy, flexibility, and digital competency (Qian, 2025; Eager & Brunton, 2023). Consequently, higher education institutions are increasingly expected to prepare students not only with disciplinary knowledge but also with the competencies necessary to effectively utilize AI technologies in academic contexts (Haroud & Saqri, 2025; Shomotova et al., 2025). In this regard, AI has become a critical competency for university students in the digital era, particularly as AI tools continue to shape learning processes, academic communication, and knowledge construction (Tzirides et al., 2024; Kamalov et al., 2023)

Within contemporary higher education, academic performance remains one of the most important indicators of student success and institutional quality (Carroza-Pacheco et al., 2025; Jiang et al., 2025). Academic performance reflects students' ability to achieve learning outcomes, adapt to academic demands, and maintain consistent educational achievement (Richardson et al., 2012). Previous studies have shown that academic performance is influenced by a wide range of cognitive, psychological, and technological factors, including motivation, self-efficacy, learning strategies, digital competence, and emotional resilience (Lin et al., 2023; Chang & Tsai, 2022; García-Martínez et al., 2022; Acosta-Gonzaga & Ramírez-Arellano, 2021; Hayat et al., 2020). In technology-enhanced learning environments, students are increasingly required to independently manage their learning activities, critically evaluate information, and effectively utilize digital tools to support academic achievement (Song et al., 2025; Shao et al., 2025). As AI-based educational technologies become more prevalent, understanding the psychological and behavioral mechanisms that contribute to academic performance has become an increasingly important research concern in educational psychology.

One factor that has recently attracted considerable scholarly attention is AI literacy. AI literacy generally refers to individuals' knowledge, understanding, and ability to effectively and ethically use AI technologies in various contexts (Ng et al., 2021). In educational settings, AI literacy encompasses students' abilities to understand AI-generated information, critically evaluate AI outputs, and integrate AI tools into academic learning processes (Chiu, 2025). Recent studies suggest that students with higher levels of AI literacy tend to demonstrate greater adaptability to digital learning environments and are more capable of utilizing technology to support problem-solving and knowledge acquisition (Bećirović et al., 2025; Lin et al., 2025; Xiao et al., 2024). Despite the growing importance of AI literacy, empirical research investigating its contribution to academic outcomes remains limited, particularly in relation to the psychological mechanisms that mediate its effects on academic performance.

In addition to technological competence, academic resilience has also emerged as an important psychological factor influencing students' academic success (Ononye et al., 2022). Academic resilience refers to students' capacity to effectively cope with academic challenges, setbacks, stress, and adverse learning conditions while maintaining motivation and educational persistence (Cassidy, 2016). In higher education contexts characterized by increasing academic demands, rapid technological changes, and post-pandemic learning adjustments, resilient students are more likely to adapt successfully and maintain stable academic engagement (Abdelrahman et al., 2025). Previous studies have consistently demonstrated that academic resilience contributes positively to learning persistence, emotional regulation, psychological well-being, and educational achievement (Egan et al., 2021; Cassidy et al., 2022; Rudd et al., 2021). Students with high academic resilience are generally more capable of overcoming academic difficulties, sustaining effort during stressful situations, and maintaining adaptive learning behaviors (Ononye et al., 2022; Etherton et al., 2020). Consequently, academic resilience has become an increasingly

relevant construct in understanding how students navigate complex learning environments in the digital era.

Another important construct closely associated with successful learning outcomes is self-regulated learning (SRL) (Shi et al., 2025). SRL refers to students' ability to proactively regulate their cognition, motivation, emotions, and behaviors in order to achieve learning goals. According to Social Cognitive Theory, self-regulated learners actively engage in goal setting, self-monitoring, strategic planning, and self-evaluation during the learning process (Zimmerman, 2000). In technology-enhanced and AI-supported educational environments, SRL plays a particularly crucial role because students are required to independently manage large amounts of information and make autonomous learning decisions. Previous research has consistently identified SRL as one of the strongest predictors of academic performance across various educational contexts (Waheed et al., 2025; García-Ros et al., 2022). Students with effective self-regulation skills tend to demonstrate higher academic persistence, stronger intrinsic motivation, and better learning outcomes compared to students with lower levels of self-regulation (Wu et al., 2024; Theobald, 2021; Ma & She, 2024). Therefore, SRL may function as a critical psychological mechanism through which technological competence and resilience contribute to academic performance.

Existing literature has attempted to examine the relationships among AI literacy, academic resilience, SRL, and academic performance. Nevertheless, most previous studies have examined these variables separately or focused only on direct relationships among constructs without adequately exploring the underlying mediating mechanisms. Despite the growing body of research on AI literacy and student learning, several important gaps remain in the literature. First, most existing studies on AI literacy primarily focus on technology acceptance, digital readiness, or ethical concerns associated with AI usage. Comparatively fewer studies have investigated how AI literacy contributes to academic performance through psychological and behavioral learning processes. Second, although academic resilience has been widely studied in relation to mental health and student well-being, limited research has examined its role in fostering self-regulated learning behaviors within AI-supported educational contexts. Third, previous studies often investigate SRL as an independent predictor of academic achievement rather than as a mediating mechanism linking technological and psychological factors to academic outcomes. Consequently, the integrated relationships among AI literacy, academic resilience, SRL, and academic performance remain underexplored, particularly among university students in developing countries.

Another limitation in prior research concerns the contextual relevance of AI-supported learning in higher education. Most empirical studies investigating AI literacy and digital learning have been conducted in technologically advanced countries with well-established digital infrastructures. However, students in developing countries may experience different challenges related to technological accessibility, digital readiness, and educational adaptation. In emerging educational contexts, students are often required to simultaneously develop digital competencies and psychological adaptability to successfully navigate rapidly changing learning environments. Therefore, investigating the interplay between AI literacy, academic resilience, and SRL in developing-country contexts may provide important insights into how students adapt to AI-driven education systems. Such investigations are particularly important for higher education institutions seeking to promote sustainable learning performance in increasingly digitalized educational environments.

The present study addresses these gaps by proposing a structural model that examines the mediating role of self-regulated learning in the relationships between AI literacy, academic resilience, and academic performance among university students. Unlike previous studies that predominantly focus on direct effects, this study positions SRL as a central psychological mechanism explaining how AI literacy and

academic resilience contribute to academic performance. Accordingly, this study aims to investigate the relationships among AI literacy, academic resilience, self-regulated learning, and academic performance among university students. Specifically, the study examines whether self-regulated learning mediates the effects of AI literacy and academic resilience on academic performance. By addressing these relationships, the study is expected to contribute to the growing literature on AI-supported education and educational psychology while offering practical implications for higher education institutions seeking to improve student learning outcomes in the era of artificial intelligence.

Based on the literature review and theoretical perspectives discussed previously, this study proposes several hypotheses regarding the relationships among AI literacy, academic resilience, self-regulated learning, and academic performance among university students. The proposed hypotheses are formulated to examine both the direct and indirect effects among the study variables within the structural equation model.

H1: AI literacy has a significant positive impact on academic performance.

H2: Academic resilience has a significant positive impact on academic performance.

H3: Self-regulated learning has a significant positive impact on academic performance.

H4: AI literacy has a significant positive impact on self-regulated learning.

H5: Academic resilience has a significant positive impact on self-regulated learning.

H6: Self-regulated learning mediates the relationship between AI literacy and academic

performance.

H7: Self-regulated learning mediates the relationship between academic resilience and academic

performance.

2. Methodology

Research Design

This study employed a quantitative research approach using a cross-sectional survey design to investigate the relationships among AI literacy, academic resilience, self-regulated learning (SRL), and academic performance among university students. A quantitative approach was considered appropriate because the study aimed to examine causal relationships among latent variables and test the mediating role of self-regulated learning within a structural model. The study utilized SEM as the primary analytical technique to simultaneously examine both measurement and structural relationships among constructs.

Participant

A total of 760 undergraduate students participated in this study using a convenience sampling technique. Participants ranged in age from 18 to 24 years old (M = 20.80, SD = 1.74). Of the participants, 520 were female students and 240 were male students. Additionally, 200 participants were enrolled in public universities, while 560 participants attended private universities in Makassar, Indonesia.

Participation in this study was entirely voluntary, and all respondents provided informed consent prior to completing the questionnaire. Participants were assured that their responses would remain anonymous and confidential and would be used solely for academic research purposes. Ethical approval for the study was obtained from the institutional research ethics committee in accordance with the Declaration of Helsinki.

Research Instrument

This study employed a structured questionnaire to measure AI literacy, academic resilience, self-regulated learning, and academic performance among university students. All instruments were adapted from internationally recognized and empirically validated scales frequently used in educational psychology and higher education research. The questionnaire utilized a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The use of short-form scales was intended to minimize respondent fatigue while maintaining satisfactory psychometric properties suitable for SEM analysis. The

instrument adaptation process followed established cross-cultural research procedures, including item selection, contextual modification, language adjustment, and content validation. Only core items with strong theoretical relevance and high factor loadings reported in previous studies were selected to ensure measurement efficiency and construct validity.

Academic Performance

To measure academic performance, this study employed the Perceived Academic Performance Scale adapted from the studies conducted by Richardson, Abraham, and Bond (2012) as well as York, Gibson, and Rankin (2015). This scale was used to assess students' perceptions of their academic achievement, learning success, and satisfaction with their academic outcomes during university study. In this study, the academic performance scale consisted of 1 dimension with a total of 4 items, as follows:

Table 1. Dimensions and Indicators of the Academic Performance Scale

Dimension	Description	Item
Academic performance	Measures students' perceptions of their academic success and learning achievement in higher education.	1, 2, 3, 4

Self-Regulated Learning

To measure self-regulated learning, this study used an adapted version of the Motivated Strategies for Learning Questionnaire (MSLQ) developed by Pintrich et al. (1991), as well as Zimmerman's (2000) self-regulated learning framework. This scale was used to assess students' ability to independently regulate their learning processes through planning, monitoring, time management, and learning evaluation activities. In this study, the self-regulated learning scale consisted of 4 dimensions with a total of 8 items, as follows:

Table 2. Dimensions and Indicators of the Self-Regulated Learning Scale

Dimension	Description	Item
Goal Setting	Measures students' ability to establish learning goals before engaging in academic activities	1, 2
Self-Monitoring	Measures students' ability to monitor their understanding and learning progress independently.	3, 4
Time Management	Measures students' ability to effectively manage study time and maintain academic discipline.	5, 6
Self-Evaluation	Measures students' ability to evaluate the effectiveness of their learning strategies.	7, 8

AI Literacy

To measure AI literacy, this study employed a scale adapted from the studies conducted by Ng et al. (2021) and Long and Magerko (2020). This scale was developed to assess individuals' ability to understand artificial intelligence concepts, critically evaluate AI-generated outputs, and effectively and ethically utilize AI technologies in learning activities. In this study, the AI literacy scale consisted of 4 dimensions with a total of 6 items, as presented below:

Table 3. Dimensions and Indicators of the AI Literacy Scale

Dimension	Description	Item
Understanding AI	Measures students' understanding of the fundamental concepts and functions of AI technologies in learning contexts.	1, 2
Evaluating AI Output	Measures students' ability to critically evaluate the accuracy and quality of AI-generated information.	3, 4
Ethical AI Use	Measures students' understanding of ethical and responsible AI use in academic settings.	5
AI-Assisted Learning	Measures students' ability to utilize AI technologies to support their learning activities.	6

Academic Resilience

To measure academic resilience, this study employed a short adaptation of the Academic Resilience Scale (ARS-30) developed by Cassidy (2016). This scale was used to assess students' ability to cope with academic pressures, maintain learning motivation, and positively adapt to difficulties encountered during the learning process. In this study, the academic resilience scale consisted of 4 dimensions with a total of 6 items, as follows:

Table 4. Dimensions and Indicators of the Academic Resilience Scale

Dimension	Description	Item
Persistence	Measures students' perseverance in completing academic tasks despite difficulties.	1, 2
Recovery from Setbacks	Measures students' ability to recover from academic failures or setbacks.	3, 4
Adaptive Response	Measures students' ability to respond positively and adaptively to academic challenges.	5
Emotional Regulation	Measures students' ability to regulate emotions when facing academic stress.	6

Data Analysis

Data analysis in this study was conducted using SEM to examine the direct and indirect relationships among AI literacy, academic resilience, self-regulated learning, and academic performance among university students. SEM is widely recognized as one of the most comprehensive statistical approaches in educational psychology, social sciences, and behavioral research because it enables researchers to simultaneously evaluate measurement models and structural relationships among latent variables (Kline, 2023; Raykov & Marcoulides, 2006).

The use of SEM was considered appropriate for this study because the proposed research model involved several latent constructs that could not be directly observed and required multiple indicators for measurement. SEM also allows for simultaneous testing of complex causal relationships, including mediation effects among variables, while accounting for measurement error. Compared to conventional regression analysis, SEM provides more accurate parameter estimation because it separates measurement error from the structural relationships among constructs (Hair et al., 2019; Kline, 2023).

This study employed the one-step (simultaneous) SEM approach by integrating the Confirmatory Factor Analysis (CFA) measurement model and the structural regression model into a single comprehensive analysis. Through this approach, the validity and reliability of the measurement indicators as well as the hypothesized relationships among variables could be evaluated simultaneously (Kline, 2023; Raykov & Marcoulides, 2006). Prior to hypothesis testing, descriptive statistics, correlation analysis, and multicollinearity diagnostics were conducted to assess the distribution and interrelationships among the study variables.

Furthermore, Confirmatory Factor Analysis (CFA) was performed to evaluate construct validity based on standardized factor loadings. The adequacy of the structural model was assessed using several goodness-of-fit indices, including Chi-square/degrees of freedom ratio (χ^2/df), Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). Following commonly accepted SEM standards, a model was considered acceptable when χ^2/df < 3.00, CFI and TLI values exceeded 0.90, RMSEA was below 0.08, and SRMR was below 0.08 (Hair et al., 2019).

3. Results

Descriptive Statistics

Table 5 presents the descriptive statistics and correlation coefficients among the study variables. Overall, the findings indicate that participants demonstrated favorable levels of academic performance (M = 11.99, SD = 3.45), self-regulated learning (M = 27.71, SD = 7.72), AI literacy (M = 12.98, SD = 2.77), and academic resilience (M = 18.01, SD = 5.10).

The correlation analysis further revealed that academic performance was positively and significantly associated with self-regulated learning ($r = 0.547$, $p < 0.01$), AI literacy ($r = 0.559$, $p < 0.01$), and academic resilience ($r = 0.451$, $p < 0.01$). These findings suggest that students with stronger self-regulated learning abilities, greater AI literacy, and better academic resilience tend to achieve better academic performance.

In addition, self-regulated learning demonstrated significant positive relationships with AI literacy ($r = 0.450$, $p < 0.01$) and academic resilience ($r = 0.355$, $p < 0.01$), indicating that students who possess stronger AI-related competencies and resilience are more likely to effectively regulate their learning processes. Furthermore, AI literacy was positively correlated with academic resilience ($r = 0.411$, $p < 0.01$), implying that students with better AI literacy also tend to exhibit stronger resilience in academic settings.

Collectively, these findings provide preliminary empirical support for the hypothesized relationships among the constructs and justify the application of SEM for further analysis.

Table 5. Descriptive Statistics and Correlation Matrix of the Study Variables

Variable	Mean	Standard Deviation	AP	SRL	AI	AR
Academic Performance (AP)	11.99	3.45	-			
Self-Regulated Learning (SRL)	27.71	7.72	0.547**	-		
AI Literacy (AI)	12.98	2.77	0.559**	0.450**	-	
Academic Resilience (AR)	18.01	5.10	0.451**	0.355	0.411	-

Note: N = 760; ** $p < 0.01$

Multicollinearity diagnostics

Prior to conducting the mediation analysis, multicollinearity assessment was performed to examine the potential intercorrelations among the independent variables. As presented in Table 6, the Variance Inflation Factor (VIF) values ranged between 1.258 to 1.379, which were substantially below the recommended cutoff threshold (VIF < 10). These findings suggest that multicollinearity was not a significant concern in the proposed model. Therefore, the results confirm the statistical suitability of the data and indicate that the regression and mediation analyses could be conducted reliably and without bias arising from collinearity issues.

Table 6. Multicollinearity Diagnostics among the Study Variables

Variable	Tolerance	VIF
Self-Regulated Learning	0.762	1.312
AI Literacy	0.725	1.379
Academic Resilience	0.795	1.258

Hypothesis Testing: Structural Equation modeling

The structural model was subsequently assessed to examine the hypothesized relationships among academic performance, self-regulated learning, AI literacy and academic resilience. To evaluate the adequacy of the proposed model, several goodness-of-fit indices were considered, including the chi-square statistic (χ^2), degrees of freedom (df), chi-square to degrees of freedom ratio (χ^2/df), Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR).

As shown in Table 7, the results indicate that the proposed structural model achieved an excellent level of fit with the observed data. Specifically, the χ^2/df ratio was 1.44, which is substantially below the recommended cut-off value of 3.00, suggesting an acceptable and parsimonious model fit. Moreover, the RMSEA value of 0.024 indicates a very close approximation between the hypothesized model and the empirical covariance matrix.

The incremental fit indices further demonstrated strong model adequacy, as evidenced by the CFI and TLI values of 0.99, both of which exceeded the recommended threshold of 0.90. In addition, the SRMR value of 0.043 was well below the acceptable limit of 0.08, indicating minimal residual discrepancies between the observed and estimated covariance matrices.

Overall, these findings confirm that the structural model adequately represents the empirical data and provides robust support for testing the hypothesized direct and indirect relationships among the study constructs.

Table 7. Goodness-of-Fit Indices for the Structural Model

Goodness-of-fit	Value
χ^2	354.576
Degree of freedom (df)	246
χ^2/df	1.44
RMSEA	0.024
CFI	0.99
TLI	0.99
SRMR	0.043

Figure 1 presents the proposed structural equation model used to examine the relationships among academic performance, self-regulated learning, AI literacy and academic resilience. The model integrates both contextual and interpersonal factors by positioning AI literacy and academic resilience as an exogenous variable, self-regulated learning as a mediating variable, and academic performance as an endogenous outcome. This model reflects the theoretical assumption that the influence of the school environment on students' well-being operates both directly and indirectly through teacher–student interactions.

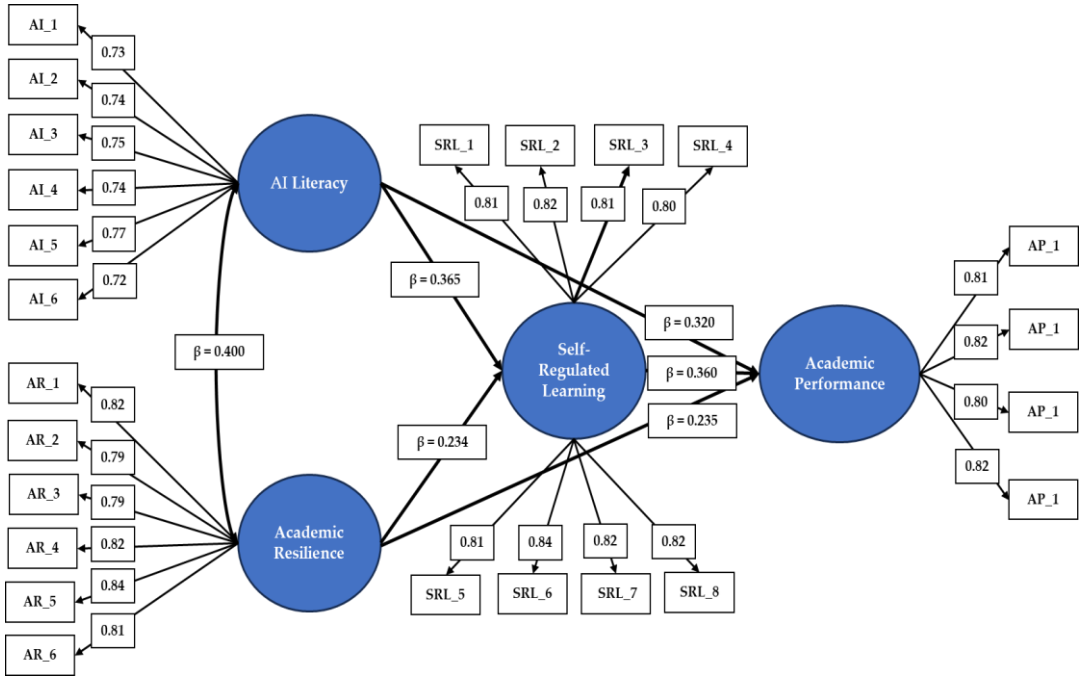

Figure 1. Structural Equation Model of the Relationships among AI Literacy, Academic Resilience, Self-Regulated Learning, and Academic Performance

Following the confirmation of the structural model adequacy, further analysis was conducted to examine both direct and indirect relationships among the study variables. This analysis aimed to evaluate the extent to which AI literacy and academic resilience influences academic performance directly as well as indirectly through self-regulated learning as a mediating variable. The results of the structural equation modeling, including standardized path coefficients and their corresponding significance levels, are presented in Table 8.

Table 8. Structural Equation Modeling Results for Direct and Indirect Effects

Pathway Type	Predictor	Self-Regulated Learning		Academic Performance	
		β	z-value	β	z-value
Direct Effect	AI Literacy	0.365	9.793	0.320	8.767
	Academic Resilience	0.234	6.267	0.235	6.882
	Self-Regulated Learning	-	-	0.360	10.504
Indirect Effect	AI Literacy → Self-Regulated Learning			0.132	7.325
	Academic resilience → Self-Regulated Learning			0.085	5.365
	R^2			**0.518 (51.8%)**	

Table 8 presents the results of the structural equation modeling analysis, including both direct and indirect effects among the study variables. The findings provide empirical support for all proposed hypotheses.

Hypothesis 1: AI Literacy → Academic Performance

Hypothesis 1 proposed that AI literacy has a significant positive impact on academic performance. The results of the structural equation modeling analysis demonstrated that AI literacy significantly and positively predicted academic performance ($\beta = 0.320$, $z = 8.767$). Therefore, Hypothesis 1 was supported. This finding indicates that students with higher levels of AI literacy tend to demonstrate better academic achievement.

Hypothesis 2: Academic Resilience → Academic Performance

Hypothesis 2 proposed that academic resilience has a significant positive impact on academic performance. The findings revealed that academic resilience significantly and positively influenced academic performance ($\beta = 0.235$, $z = 6.882$). Thus, Hypothesis 2 was supported. This result suggests that students who are more resilient in coping with academic challenges are more likely to achieve higher academic performance.

Hypothesis 3: Self-Regulated Learning → Academic Performance

Hypothesis 3 proposed that self-regulated learning has a significant positive impact on academic performance. The analysis showed that self-regulated learning significantly predicted academic performance ($\beta = 0.360$, $z = 10.504$). Therefore, Hypothesis 3 was supported. This finding confirms the important role of self-regulated learning in enhancing students' academic success.

Hypothesis 4: AI Literacy → Self-Regulated Learning

Hypothesis 4 proposed that AI literacy has a significant positive impact on self-regulated learning. The results indicated that AI literacy significantly and positively influenced self-regulated learning ($\beta = 0.365$, $z = 9.793$). Accordingly, Hypothesis 4 was supported. This finding suggests that students with stronger AI-related competencies are more capable of independently regulating their learning processes.

Hypothesis 5: Academic Resilience → Self-Regulated Learning

Hypothesis 5 proposed that academic resilience has a significant positive impact on self-regulated learning. The findings demonstrated that academic resilience significantly predicted self-regulated learning ($\beta = 0.234$, $z = 6.267$). Therefore, Hypothesis 5 was supported. This result indicates that resilient students are more likely to exhibit effective self-regulated learning behaviors.

Hypothesis 6: AI Literacy → Self-Regulated Learning → Academic Performance

Hypothesis 6 proposed that self-regulated learning mediates the relationship between AI literacy and academic performance. The mediation analysis revealed that self-regulated learning significantly mediated the relationship between AI literacy and academic performance ($\beta = 0.132$, $z = 7.325$). Thus, Hypothesis 6 was supported. This finding implies that AI literacy contributes to academic performance both directly and indirectly through self-regulated learning.

Hypothesis 7: Academic Resilience → Self-Regulated Learning → Academic Performance

Hypothesis 7 proposed that self-regulated learning mediates the relationship between academic resilience and academic performance. The results showed that self-regulated learning significantly mediated the relationship between academic resilience and academic performance ($\beta = 0.085$, $z = 5.365$). Therefore, Hypothesis 7 was supported. This finding indicates that academic resilience contributes to academic achievement through the enhancement of students' self-regulated learning abilities.

The coefficient of determination (R^2) analysis revealed that the proposed structural model

explained 51.8% of the variance in academic performance ($R^2 = 0.518$). This finding indicates that AI literacy, academic resilience, and self-regulated learning collectively contributed substantially to students' academic achievement. According to Cohen's classification, the obtained R^2 value can be considered moderate to substantial, suggesting that the model possesses strong explanatory power in predicting academic performance among university students. These results further demonstrate that both technological competence and psychological learning factors play important roles in supporting students' academic success within AI-supported educational environments.

Table 9 presents the standardized factor loadings and z-values for all measurement items used in the study. Overall, the findings indicate that all indicators demonstrated satisfactory psychometric properties and adequately represented their respective latent constructs. The standardized factor loadings ranged from 0.721 to 0.842, exceeding the recommended minimum threshold of 0.50, thereby indicating acceptable convergent validity of the measurement model (Hair et al., 2019). Specifically, the academic performance scale demonstrated strong factor loadings ranging from 0.806 to 0.824, indicating that all items consistently reflected students' perceptions of academic achievement. Similarly, the self-regulated learning scale showed high factor loadings ranging from 0.807 to 0.841, suggesting that the indicators effectively measured students' abilities related to goal setting, self-monitoring, time management, and self-evaluation.

Furthermore, the AI literacy scale exhibited acceptable factor loadings ranging from 0.721 to 0.771, indicating that the items adequately captured students' understanding, evaluation, and utilization of AI technologies in learning contexts. The academic resilience scale also demonstrated strong factor loadings ranging from 0.790 to 0.842, reflecting the robustness of the indicators in measuring students' persistence, adaptive responses, and emotional regulation in academic situations.

In addition, all measurement items produced statistically significant z-values, further confirming the validity and reliability of the indicators within the measurement model. Collectively, these findings indicate that the measurement model possesses satisfactory construct validity and is appropriate for subsequent structural equation modeling analysis.

Table 9. Standardized Factor Loadings and z-values of the Measurement Items

Scale	Item	Loading Factor	z-value
Academic Performance	I achieve satisfactory academic results	0.813	53.734
	My academic performance meets my expectations	0.821	55.796
	I perform well in most of my courses	0.806	52.185
	I am satisfied with my academic achievement	0.824	56.646
Self-Regulated learning	I set learning goals before studying.	0.811	59.512
	I organize my study activities effectively.	0.815	60.578
	I monitor my understanding while learning.	0.813	59.991
	I review my academic progress regularly.	0.807	58.067
	I manage my study time efficiently.	0.841	70.655
	I stay disciplined in completing academic tasks.	0.810	59.216
	I evaluate whether I have learned successfully.	0.840	70.270
	I adjust my learning strategies when necessary.	0.822	63.082
AI Literacy	I understand how AI tools generate information.	0.733	36.852
	I understand the basic functions of AI technologies in learning.	0.746	38.779
	I can evaluate whether AI-generated information is accurate.	0.752	39.640

	I critically assess information produced by AI systems.	0.743	38.281
	I understand the ethical limitations of using AI in academic work.	0.771	42.708
	I can effectively use AI tools to support my learning activities.	0.721	12.900
Academic Resilience	I remain motivated despite academic difficulties.	0.822	60.365
	I persist even when learning tasks are difficult.	0.790	51.103
	I can recover quickly after receiving poor grades.	0.794	52.153
	I believe I can overcome academic setbacks.	0.821	60.034
	Academic challenges encourage me to work harder.	0.842	67.084
	I stay focused during stressful academic situations.	0.812	57.084

4. Discussion

The present study investigated the relationships among AI literacy, academic resilience, self-regulated learning (SRL), and academic performance among university students within AI-supported higher education environments. The findings demonstrated that AI literacy, academic resilience, and self-regulated learning significantly contributed to academic performance, while self-regulated learning also functioned as a significant mediating mechanism in the relationships between AI literacy, academic resilience, and academic performance. Overall, these findings provide empirical support for the integration of Social Cognitive Theory, Resilience Theory, and digital competency perspectives in explaining students' academic adaptation in increasingly technology-enhanced learning environments.

First, the findings revealed that AI literacy significantly and positively predicted academic performance. This result suggests that students with stronger AI-related competencies tend to demonstrate higher academic achievement. The finding supports previous studies indicating that AI literacy enhances students' ability to access information efficiently, critically evaluate digital content, and utilize AI technologies to support learning activities (Ng et al., 2021; Lin et al., 2025). In contemporary higher education contexts, AI technologies such as generative AI systems, intelligent tutoring platforms, and automated learning assistants increasingly influence how students process knowledge and complete academic tasks (Qian, 2025). Students with higher levels of AI literacy may therefore possess greater flexibility and autonomy in managing academic demands. This finding is also consistent with previous research showing that digital competence positively contributes to learning effectiveness and academic achievement in technology-enhanced educational settings (Shao et al., 2025). From a Social Cognitive Theory perspective, technologically competent students are more likely to develop stronger self-efficacy beliefs and adaptive learning behaviors, which subsequently facilitate academic success (Bandura, 1986).

Second, the findings demonstrated that academic resilience significantly and positively influenced academic performance. This result indicates that resilient students are more capable of coping with academic stress, overcoming learning difficulties, and maintaining persistence in challenging educational situations. The finding aligns with previous studies emphasizing the important role of resilience in promoting academic adaptation, emotional regulation, and educational achievement among university students (Cassidy, 2016; Ononye et al., 2022). In higher education environments characterized by rapid technological changes and increasing academic complexity, resilience becomes an essential psychological resource that helps students maintain motivation and engagement despite academic setbacks. Students with stronger resilience are generally more capable of adapting to uncertainty and sustaining academic effort during stressful learning experiences (Rudd et al., 2021). This finding further supports Resilience Theory, which suggests that adaptive coping mechanisms and psychological persistence are important determinants of successful educational outcomes.

Third, self-regulated learning was found to significantly predict academic performance. This finding confirms the central role of SRL in facilitating successful learning outcomes in higher education contexts. Students who effectively regulate their learning processes through goal setting, self-monitoring, time management, and self-evaluation tend to demonstrate stronger academic achievement. This result is consistent with extensive previous literature identifying SRL as one of the strongest predictors of academic success across various educational settings (Pintrich et al., 1991; Zimmerman, 2000; Richardson et al., 2012). In AI-supported learning environments, SRL becomes increasingly important because students are required to independently manage information overload, evaluate the credibility of AI-generated content, and make autonomous learning decisions (Ma & She, 2024). The findings also support the argument proposed by Lin et al. (2023) that students with stronger self-regulation strategies are more likely to demonstrate adaptive learning behaviors and higher academic persistence during higher education transitions.

Furthermore, the results indicated that AI literacy significantly predicted self-regulated learning. This finding suggests that students with stronger AI-related competencies are more capable of independently regulating their learning activities. Students who understand how AI technologies function and how to critically utilize AI-generated information may be more confident in managing learning tasks, organizing study strategies, and evaluating their own academic progress. This finding is consistent with studies suggesting that digital competence and AI literacy contribute positively to autonomous learning and learning engagement (Ng et al., 2021; Lin et al., 2025). In technology-rich educational environments, AI literacy may function not only as a technical competency but also as a cognitive resource that supports effective self-management and adaptive learning behaviors.

Similarly, academic resilience was found to significantly predict self-regulated learning. This result indicates that resilient students are more likely to engage in effective learning regulation behaviors, including maintaining focus, managing academic stress, and adjusting learning strategies when encountering difficulties. Students with high resilience may possess stronger emotional control and greater persistence, enabling them to remain engaged in learning activities despite academic challenges. This finding supports previous research demonstrating positive relationships between resilience, learning persistence, and self-regulatory behaviors (Cassidy, 2016; Rudd et al., 2021). From a psychological perspective, resilient students may develop stronger motivational regulation and adaptive coping strategies that facilitate independent learning processes.

One of the most important findings of this study concerns the mediating role of self-regulated learning in the relationships between AI literacy, academic resilience, and academic performance. The results demonstrated that self-regulated learning significantly mediated the influence of AI literacy on academic performance. This finding implies that students' AI competencies contribute to academic achievement not only directly but also indirectly through enhanced learning regulation abilities. Students who effectively utilize AI technologies may become more strategic, reflective, and autonomous learners, which subsequently improves their academic outcomes. This finding extends previous studies that primarily focused on the direct effects of technological competence on academic achievement without adequately examining the underlying psychological mechanisms (Ng et al., 2021; Lin et al., 2025; Shao et al., 2025). The findings also support Social Cognitive Theory, which emphasizes that cognitive competencies and self-regulatory processes jointly influence learning outcomes (Bandura, 1986; Zimmerman, 2000).

Likewise, self-regulated learning significantly mediated the relationship between academic resilience and academic performance. This finding suggests that resilient students achieve stronger academic outcomes because they are better able to regulate their learning processes, maintain motivation, and adapt learning strategies during academic challenges. The result reinforces

the theoretical assumption that resilience contributes to academic achievement through adaptive behavioral and cognitive processes rather than through direct psychological endurance alone. This finding also highlights the importance of integrating psychological resilience and self-regulatory learning perspectives in understanding students' academic success within rapidly changing educational environments (Cassidy, 2016; Rudd et al., 2021). Previous studies have similarly reported that resilient students tend to demonstrate stronger persistence, learning engagement, and adaptive coping strategies that positively influence academic achievement (Ononye et al., 2022; Lin et al., 2023).

The findings of this study offer several important theoretical contributions to educational psychology literature. First, this study extends existing research by integrating AI literacy, academic resilience, and self-regulated learning within a single structural framework explaining academic performance in AI-enhanced higher education contexts. Second, the study provides empirical support for the integration of Social Cognitive Theory and Resilience Theory in explaining how technological and psychological factors jointly contribute to students' academic adaptation. Third, the identification of self-regulated learning as a mediating mechanism contributes to a more comprehensive understanding of how AI-related competencies and resilience influence academic achievement indirectly through behavioral learning processes (Bandura, 1986; Zimmerman, 2000; Cassidy, 2016). These findings also enrich the growing literature on AI-supported education, particularly regarding the importance of combining technological readiness and psychological adaptability in promoting sustainable academic success among university students (Ng et al., 2021; Qian, 2025).

Despite its important contributions, this study has several limitations that should be acknowledged. First, the study employed a cross-sectional design, which limits the ability to establish causal relationships among AI literacy, academic resilience, self-regulated learning, and academic performance. Future studies are therefore encouraged to utilize longitudinal or experimental designs to better examine the dynamic relationships among these variables over time. Second, the participants were recruited only from universities in Makassar, Indonesia, which may limit the generalizability of the findings to other educational and cultural contexts. Finally, this study focused primarily on psychological and technological factors without considering additional contextual variables such as institutional support, socioeconomic background, or learning environment characteristics that may also influence students' academic performance in AI-supported education settings.

5. Conclusion

In conclusion, this study demonstrates that AI literacy, academic resilience, and self-regulated learning play significant roles in enhancing university students' academic performance within AI-supported higher education environments. The findings revealed that AI literacy and academic resilience not only directly contributed to academic achievement but also indirectly influenced academic performance through self-regulated learning as a significant mediating mechanism. These results highlight the importance of integrating technological competencies and psychological adaptability in promoting successful learning outcomes in the digital era. The study further contributes to educational psychology literature by providing an integrated structural framework that explains how AI-related competencies and resilience jointly support students' academic adaptation through self-regulatory learning processes. Practically, the findings suggest that higher education institutions should prioritize the development of AI literacy, resilience, and self-regulated learning skills to support sustainable academic success in increasingly technology-enhanced educational contexts.

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Author Declaration

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