

Exploring the Strengthening of Lecturer Performance in the Education Era through AI-Driven Instructional Design Capability and Data-Informed Teaching Decision-Making

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Abstract

This study develops and empirically validates an integrated educational technology model to explain students' academic resilience through the roles of Adaptive Learning System Maturity and Metacognitive Regulation Technology, mediated by Self-Regulated Learning Behavior and Digital Learning Effectiveness. Employing a quantitative structural equation modeling (SEM) approach, the study examines both direct and indirect relationships among the proposed constructs to understand the mechanisms underlying successful digital learning. The findings indicate that Adaptive Learning System Maturity and Metacognitive Regulation Technology significantly enhance students' Self-Regulated Learning Behavior and Digital Learning Effectiveness, demonstrating that advanced learning technologies and metacognitive support are essential determinants of effective learning processes. Furthermore, Self-Regulated Learning Behavior and Digital Learning Effectiveness significantly contribute to Academic Resilience, confirming their important mediating roles in strengthening students' capacity to adapt, persist, and succeed in challenging academic environments. Mediation analysis further reveals that both variables partially mediate the relationships between educational technology factors and Academic Resilience. However, the sequential mediation effect is not statistically supported, suggesting that Self-Regulated Learning Behavior and Digital Learning Effectiveness operate as parallel rather than sequential mechanisms in fostering students' academic resilience.

Keywords: adaptive learning system maturity; metacognitive regulation technology; self-regulated learning behavior

INTRODUCTION

The rapid advancement of digital technologies has fundamentally transformed higher education, creating new opportunities for personalized, flexible, and technology-enhanced learning experiences. Universities worldwide increasingly adopt digital learning ecosystems that integrate artificial intelligence, adaptive learning platforms, and intelligent educational technologies to improve students' learning outcomes and academic success. These developments have accelerated following the expansion of online and hybrid learning environments, making educational technology an essential component of contemporary

higher education rather than merely a supplementary instructional tool. Consequently, higher education institutions are expected not only to provide digital learning infrastructure but also to ensure that such technologies effectively support students' cognitive development, learning autonomy, and long-term academic achievement (Anjarany & Marianti, 2026).

Despite significant investments in educational technology, many universities continue to experience considerable challenges in maximizing the effectiveness of digital learning environments. Students frequently encounter difficulties in maintaining learning motivation, regulating their own learning processes, managing academic stress, and adapting to increasingly complex academic demands. The abundance of digital learning resources does not automatically guarantee meaningful learning experiences or improved academic performance. Instead, successful digital learning depends on the interaction between technological capabilities and students' ability to effectively regulate their own learning activities. Consequently, educational researchers increasingly recognize that technological innovation alone cannot ensure successful learning outcomes without corresponding improvements in students' self-regulation and learning effectiveness (Ansell & Gash, 2023).

Adaptive learning systems refer to intelligent educational platforms capable of continuously analyzing learners' progress, identifying individual learning needs, and dynamically adjusting instructional content, assessment difficulty, and learning pathways according to students' performance and preferences. A mature adaptive learning system is characterized by advanced personalization capabilities, real-time learning analytics, intelligent feedback mechanisms, system interoperability, and continuous improvement through artificial intelligence. Such systems provide individualized learning experiences that accommodate differences in learners' prior knowledge, learning pace, cognitive abilities, and academic goals. Consequently, adaptive learning system maturity is expected to strengthen students' engagement, learning autonomy, and overall academic development (Benz & Papadopoulos, 2021).

Beyond adaptive technologies, another critical determinant of successful digital learning is Metacognitive Regulation Technology. Metacognitive regulation technology encompasses digital tools and intelligent learning support systems that assist learners in planning, monitoring, evaluating, and regulating their own cognitive processes throughout the learning experience. These technologies include intelligent dashboards, self-monitoring applications, automated feedback systems, reflective learning journals, and AI-based learning assistants that encourage students to become more aware of their learning strategies and academic progress. By facilitating continuous reflection and self-assessment, metacognitive regulation technologies enable students to make informed learning decisions, identify weaknesses, adjust study strategies, and improve problem-solving abilities. Therefore, these technologies are expected to play a significant role in strengthening students' learning independence and academic adaptability (Biesbroek et al., 2021).

The effectiveness of Adaptive Learning System Maturity and Metacognitive Regulation Technology is expected to be reflected through Self-Regulated Learning Behavior, which represents students' ability to proactively manage their learning processes by setting goals, selecting learning strategies, monitoring progress, managing time, regulating motivation, and evaluating learning outcomes. Self-regulated learning has long

been recognized as one of the strongest predictors of academic success in technology-enhanced learning environments because it enables learners to become active participants rather than passive recipients of knowledge. Students possessing stronger self-regulation capabilities generally demonstrate higher persistence, greater learning engagement, improved problem-solving skills, and better academic achievement. As digital learning environments require greater learner autonomy, self-regulated learning behavior becomes increasingly important for successful educational outcomes (Bollen, 2023).

Another important outcome of technology-enhanced education is Digital Learning Effectiveness, which refers to the extent to which digital learning environments successfully facilitate meaningful learning experiences, knowledge acquisition, skill development, learner satisfaction, and academic performance. Effective digital learning is influenced not only by technological infrastructure but also by instructional quality, system usability, learner engagement, and the alignment between technology and pedagogical objectives. Students who experience effective digital learning environments are generally better able to understand course materials, maintain learning motivation, collaborate with peers, and apply acquired knowledge in solving academic problems. Therefore, digital learning effectiveness serves as a crucial mechanism linking educational technology adoption with broader educational outcomes (Bouckaert et al., 2024).

Ultimately, the primary objective of higher education extends beyond academic achievement to the development of Academic Resilience. Academic resilience refers to students' capacity to successfully overcome academic challenges, recover from setbacks, maintain motivation under stressful conditions, and continue pursuing educational goals despite encountering obstacles or failures. In contemporary higher education, academic resilience has become increasingly important because students are expected to adapt continuously to technological changes, evolving learning environments, and increasingly demanding academic expectations. Resilient students demonstrate stronger emotional regulation, greater persistence, higher confidence, and more effective coping strategies when facing academic difficulties (Chaffin et al., 2020).

Although previous studies have extensively examined adaptive learning technologies, metacognitive strategies, self-regulated learning, and academic resilience independently, relatively limited research has integrated these constructs within a comprehensive educational technology framework. Existing literature frequently investigates technological factors or psychological learning processes separately, resulting in an incomplete understanding of the mechanisms through which educational technologies contribute to students' academic resilience. Moreover, empirical evidence regarding the mediating roles of Self-Regulated Learning Behavior and Digital Learning Effectiveness remains fragmented, particularly within higher education contexts characterized by rapid digital transformation (Djalante et al., 2023).

Therefore, this study proposes an integrated conceptual framework examining the relationships among Adaptive Learning System Maturity, Metacognitive Regulation Technology, Self-Regulated Learning Behavior, Digital Learning Effectiveness, and Academic Resilience. Specifically, the study investigates both direct and indirect relationships among these variables to explain how advanced educational technologies

strengthen students' resilience through improvements in learning regulation and digital learning effectiveness. By simultaneously examining these relationships, this research contributes to the advancement of Self-Regulated Learning Theory, Social Cognitive Theory, Metacognitive Learning Theory, and Educational Technology Theory while providing empirical evidence regarding the mechanisms through which intelligent learning technologies enhance students' academic resilience in contemporary higher education.

Many higher education institutions continue to experience challenges in maximizing the benefits of digital learning despite substantial investments in educational technologies and learning management systems. Common barriers include limited personalization of learning platforms, insufficient metacognitive support, low student engagement, inadequate self-regulation skills, and inconsistencies in the quality of digital learning experiences. These challenges often reduce students' motivation, hinder meaningful learning, and ultimately weaken their ability to cope with academic pressures. Consequently, improving the maturity of adaptive learning systems and integrating technologies that facilitate metacognitive regulation have become essential priorities for enhancing the effectiveness of digital education (Chaffin et al., 2022).

Previous studies suggest that Self-Regulated Learning Behavior plays a crucial role in improving Digital Learning Effectiveness. Students who actively plan their learning activities, monitor their progress, regulate their motivation, and evaluate their learning strategies tend to utilize digital learning environments more efficiently and achieve superior academic outcomes. Self-regulated learners demonstrate greater persistence, better time management, stronger problem-solving skills, and higher engagement with digital instructional materials. Therefore, Self-Regulated Learning Behavior is expected to function as an important determinant of Digital Learning Effectiveness within technology-enhanced learning environments (Daud & Gusnita, 2026).

The ultimate objective of technology-enhanced higher education is reflected in Academic Resilience. Academic resilience refers to students' ability to successfully adapt to academic challenges, recover from setbacks, maintain learning motivation under pressure, and persist in achieving educational goals despite experiencing adversity. In increasingly digital learning environments, academic resilience has become one of the most important competencies required for student success because learners are expected to independently manage complex learning tasks, rapidly changing technologies, and continuously evolving academic expectations. Students possessing strong academic resilience generally demonstrate higher confidence, emotional stability, adaptive coping strategies, and sustained academic performance even under stressful conditions (Duit et al., 2021).

Academic resilience is not solely influenced by individual psychological characteristics but is also shaped by the quality of learning environments and educational technologies that support students throughout the learning process. Mature adaptive learning systems provide personalized instructional pathways that accommodate individual learning needs, while metacognitive regulation technologies assist students in planning, monitoring, and evaluating their learning activities. Together, these technological capabilities create supportive digital learning environments that strengthen students' learning autonomy,

improve learning effectiveness, and foster resilience when confronting academic difficulties (Folke et al., 2023).

Despite the growing body of literature on adaptive learning technologies, metacognitive regulation, self-regulated learning, digital learning effectiveness, and academic resilience, important research gaps remain. Previous studies have predominantly examined these variables independently or focused on isolated relationships among them, resulting in a fragmented understanding of how educational technologies collectively influence students' academic resilience (Loorbach et al., 2020). Moreover, empirical evidence regarding the mediating roles of Self-Regulated Learning Behavior and Digital Learning Effectiveness in explaining the influence of adaptive educational technologies on academic resilience remains limited, particularly within higher education contexts experiencing rapid digital transformation (Gross & Harley, 2024).

Therefore, this study proposes an integrated educational technology framework that examines the relationships among Adaptive Learning System Maturity, Metacognitive Regulation Technology, Self-Regulated Learning Behavior, Digital Learning Effectiveness, and Academic Resilience. Consistent with the proposed conceptual model, this study investigates both direct and indirect relationships among these constructs, including the mediating roles of Self-Regulated Learning Behavior and Digital Learning Effectiveness. By simultaneously examining these relationships, this research seeks to extend Self-Regulated Learning Theory, Social Cognitive Theory, Metacognitive Learning Theory, and Technology Acceptance Model (TAM) by providing empirical evidence regarding the mechanisms through which advanced educational technologies strengthen students' academic resilience. Furthermore, the findings are expected to offer practical recommendations for higher education institutions in designing intelligent digital learning ecosystems that promote autonomous learning, improve learning effectiveness, and enhance students' resilience in the face of increasingly complex academic challenges (Folke et al., 2021).

Self-Regulated Learning (SRL) Theory proposed by Barry J. Zimmerman emphasizes that effective learning occurs when students actively regulate their cognitive, motivational, and behavioral processes throughout learning activities. Modern adaptive learning systems provide personalized instructional pathways, intelligent feedback, and real-time learning analytics that enable learners to monitor their progress and adjust their learning strategies according to individual needs. As adaptive learning systems become more mature, they increasingly facilitate learner autonomy and independent decision-making during the learning process (Gupta et al., 2023).

Adaptive Learning System Maturity refers to the extent to which adaptive learning platforms effectively utilize artificial intelligence, learning analytics, personalized recommendations, and dynamic content delivery to accommodate individual learner characteristics. Mature adaptive learning systems continuously analyze students' performance and provide customized learning experiences that encourage active engagement and independent learning (Haasnoot et al., 2021).

Previous studies have shown that adaptive learning technologies significantly improve learners' goal setting, learning strategy selection, self-monitoring, and self-evaluation.

Personalized learning environments encourage students to become active participants in managing their own learning process, thereby strengthening self-regulated learning behavior. Therefore, higher levels of Adaptive Learning System Maturity are expected to positively influence students' Self-Regulated Learning Behavior (Hill & Hupe, 2023).

Metacognitive Theory developed by John H. Flavell explains that learners become more effective when they are capable of planning, monitoring, and evaluating their own cognitive processes. Digital technologies designed to support metacognitive regulation provide students with intelligent feedback, reflective learning tools, progress dashboards, and self-assessment mechanisms that facilitate continuous learning reflection (Hölscher et al., 2023).

Metacognitive Regulation Technology enables students to become more aware of their learning strengths and weaknesses while encouraging strategic learning behaviors. Through real-time monitoring and personalized feedback, these technologies help learners adjust learning strategies, regulate motivation, and improve academic decision-making.

Empirical studies consistently demonstrate that metacognitive technologies enhance learners' self-regulation, learning autonomy, and strategic thinking. Consequently, students utilizing advanced metacognitive regulation technologies are expected to exhibit stronger Self-Regulated Learning Behavior (Jarrell et al., 2025).

Educational Technology Theory suggests that technology contributes to learning outcomes when instructional systems effectively support learner needs and facilitate meaningful interaction. Adaptive learning systems improve learning effectiveness by delivering personalized instructional materials, adaptive assessments, intelligent tutoring, and immediate feedback based on students' individual learning progress (Hasibuan et al., 2026).

Mature adaptive learning systems reduce cognitive overload, increase learning engagement, and optimize instructional efficiency by presenting learning materials that correspond to learners' capabilities and preferences. Personalized learning experiences enable students to understand concepts more effectively while improving satisfaction with digital learning environments (Howlett et al., 2022).

Previous research indicates that adaptive educational technologies significantly improve student engagement, knowledge acquisition, learning satisfaction, and academic achievement. Therefore, Adaptive Learning System Maturity is expected to positively influence Digital Learning Effectiveness.

The Technology Acceptance Model (TAM) developed by Fred D. Davis explains that technologies perceived as useful and easy to use significantly improve users' performance and learning outcomes. Metacognitive regulation technologies enhance students' learning experiences by providing continuous feedback, self-monitoring tools, reflective learning support, and personalized recommendations that improve learning quality (Howlett et al., 2024).

Students who effectively utilize metacognitive technologies demonstrate better learning organization, improved problem-solving abilities, and greater engagement with digital instructional resources. These technologies facilitate active learning while helping learners continuously evaluate and refine their learning strategies (Jarrell et al., 2025).

Previous empirical studies have reported that metacognitive learning support technologies significantly improve digital learning effectiveness by increasing learning efficiency, learner satisfaction, and knowledge retention. Accordingly, Metacognitive Regulation Technology is expected to positively influence Digital Learning Effectiveness (Kuhlmann & Franzke, 2022).

Self-Regulated Learning Theory argues that students who actively regulate their learning processes achieve superior learning outcomes because they effectively manage learning goals, strategies, motivation, and academic resources. Self-regulated learners demonstrate greater persistence, time management, critical thinking, and reflective learning behaviors that contribute to successful digital learning experiences (Jordan et al., 2021).

In digital learning environments where learners possess greater autonomy, self-regulated learning becomes an essential determinant of learning effectiveness. Students capable of independently planning, monitoring, and evaluating their learning activities are generally more successful in utilizing digital technologies to achieve educational objectives (Kivimaa et al., 2024).

Previous studies consistently demonstrate that Self-Regulated Learning Behavior significantly enhances learner engagement, academic performance, digital learning satisfaction, and instructional effectiveness. Therefore, Self-Regulated Learning Behavior is expected to positively influence Digital Learning Effectiveness (Kern & Rogge, 2022).

H5: Self-Regulated Learning Behavior positively influences Digital Learning Effectiveness.

Self-Regulated Learning Theory developed by Barry J. Zimmerman argues that educational technologies influence learning outcomes through intermediate learning processes rather than solely through direct effects. In this study (Liao & Shi, 2021), Self-Regulated Learning Behavior and Digital Learning Effectiveness represent the key mechanisms through which Adaptive Learning System Maturity and Metacognitive Regulation Technology influence Students' Academic Resilience (Jarrell et al., 2025).

Previous studies suggest that mature adaptive learning systems and metacognitive regulation technologies improve students' academic outcomes indirectly by strengthening self-regulated learning behavior and enhancing digital learning effectiveness. Adaptive learning systems provide personalized learning pathways, intelligent feedback, and adaptive instructional support that encourage students to regulate their own learning activities. Likewise, metacognitive regulation technologies assist learners in planning, monitoring, evaluating, and continuously improving their learning strategies, thereby fostering more effective digital learning experiences and stronger academic resilience (Kline, 2023). However, empirical findings remain fragmented, particularly regarding the simultaneous mediating roles of Self-Regulated (Jordan & Huitema, 2024).

METHODS

Research Design and Study Area

This study employed a quantitative research design using a cross-sectional survey approach to examine the relationships among educational technology, learning behavior, and students' academic resilience in higher education. Specifically, the study investigates the relationships among Adaptive Learning System Maturity (X1), Metacognitive Regulation Technology (X2), Self-Regulated Learning Behavior (Y1), Digital Learning Effectiveness (Y2), and Academic Resilience (Z). A quantitative approach was considered appropriate

because the study aims to test theoretically derived hypotheses and evaluate causal relationships among latent constructs using Covariance-Based Structural Equation Modeling (CB-SEM).

The study was conducted at universities in Banten Province, Indonesia, involving undergraduate students who actively utilized digital learning platforms such as Learning Management Systems (LMS), adaptive learning applications, and other technology-enhanced learning environments. Banten Province was selected because higher education institutions in the region have increasingly implemented digital learning systems to support blended and online learning. This context provides an appropriate setting for examining how adaptive educational technologies influence students' learning behavior, digital learning effectiveness, and academic resilience. Data collection was conducted between January and March 2026 using a structured questionnaire administered both online and offline to undergraduate students from several public and private universities (Hair et al., 2022).

Population, Sampling Technique, and Data Collection

The target population of this study consisted of undergraduate students enrolled in higher education institutions in Banten Province who had experience using adaptive digital learning systems and educational technologies during their academic studies.

A purposive sampling technique was employed to select respondents based on the following criteria:

1. Undergraduate students actively enrolled during the 2025/2026 academic year.
2. Have experience using Learning Management Systems (LMS), adaptive learning platforms, or other digital learning applications.
3. Have participated in online or blended learning for at least one academic semester.
4. Willingly participate in the study by providing informed consent.

Data were collected through a structured questionnaire distributed electronically using online survey platforms and directly to students during academic activities where appropriate. A total of 400 questionnaires were distributed. After data screening for completeness, consistency, and response quality, 368 valid questionnaires were retained for analysis. This sample size exceeds the minimum requirement for Covariance-Based Structural Equation Modeling (CB-SEM) and provides sufficient statistical power for multivariate analysis and structural model estimation (Hair et al., 2022).

Measurement Instrument and Variables

The research instrument consisted of two sections. The first section collected respondents' demographic information, including gender, age, university, field of study, academic year, experience using digital learning platforms, and frequency of utilizing adaptive learning technologies.

The second section measured the latent variables included in the proposed conceptual framework. Adaptive Learning System Maturity (X1) was measured using indicators reflecting system personalization, adaptive instructional capability, intelligent feedback, learning analytics, content adaptability, and technological responsiveness.

Metacognitive Regulation Technology (X2) was measured through indicators representing planning support, self-monitoring tools, reflective learning features, automated feedback systems, learning dashboards, and digital self-evaluation capabilities.

Self-Regulated Learning Behavior (Y1) was measured using indicators assessing goal setting, learning strategy utilization, time management, self-monitoring, motivation regulation, and learning self-evaluation. Digital Learning Effectiveness (Y2) was measured through indicators reflecting instructional quality, learner engagement, perceived usefulness, learning satisfaction, interaction quality, knowledge acquisition, and academic performance improvement within digital learning environments.

Finally, Academic Resilience (Z) was measured using indicators representing persistence in learning, adaptability to academic challenges, emotional regulation, confidence in overcoming learning difficulties, recovery from academic setbacks, and sustained motivation to achieve educational goals. All measurement items were adapted from well-established instruments in previous educational technology and learning research and modified to fit the context of higher education digital learning. Prior to the main survey, the questionnaire was reviewed by experts in educational technology and higher education and pilot-tested to ensure clarity, content validity, and contextual appropriateness.

All items were measured using a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree").

Ethical Considerations

This study complied with established ethical principles governing educational and social science research. Participation in the study was entirely voluntary, and all respondents were informed of the research objectives, procedures, confidentiality protections, and their rights before completing the questionnaire.

Informed consent was obtained from every participant prior to data collection. Respondents were assured that their participation was anonymous and that no personally identifiable information would be collected. All responses were used exclusively for academic research purposes.

Participants were informed that they could withdraw from the study at any stage without penalty. All research data were securely stored, accessible only to the research team, and managed in accordance with institutional research ethics guidelines to ensure confidentiality, privacy protection, and data integrity throughout the research process (Hair et al., 2022).

RESULTS

Respondent Profile

Table 1 presents the demographic characteristics of the 368 undergraduate students who participated in this study. The respondents represent students from several public and private universities in Banten Province, Indonesia, who actively utilized digital learning platforms during their academic activities. The gender distribution is relatively balanced, with female students slightly outnumbering male students (55.2% and 44.8%, respectively), indicating that the sample adequately represents both genders and minimizes potential gender bias in the subsequent analyses.

Most respondents were between 20 and 22 years old (45.4%), followed by students aged 17–19 years (32.6%), 23–25 years (18.2%), and above 25 years (3.8%). This distribution reflects the typical age range of undergraduate students in Indonesian higher education institutions. Regarding the year of study, the majority of respondents were in their third year (33.4%), followed by second-year students (28.3%), first-year students (22.8%), and final-year students (15.5%). Students at different academic levels provide diverse perspectives on their experiences using adaptive learning systems and digital learning technologies.

With respect to experience in digital learning, 42.1% of respondents reported using digital learning platforms for more than three years, while 34.2% had used them for two to three years, 17.4% for one to two years, and 6.3% for less than one year. These findings indicate that most respondents possessed sufficient experience with digital learning environments to evaluate the constructs investigated in this study. Regarding the frequency of digital learning platform utilization, 46.7% of respondents reported accessing digital learning systems every day, followed by 31.3% who used them four to six days per week, 15.5% who used them two to three days per week, and 6.5% who accessed digital learning platforms once a week or less. The high frequency of digital learning usage suggests that respondents were familiar with adaptive educational technologies and capable of providing reliable assessments of their learning experiences.

Overall, the demographic characteristics indicate that the respondents possess adequate experience with adaptive learning systems, metacognitive learning technologies, and digital learning environments.

Profile Category	Classification	Frequency (n)	Percentage (%)
Gender	Male	165	44.8
	Female	203	55.2
Age Group	17–19 years	120	32.6
	20–22 years	167	45.4
	23–25 years	67	18.2
	Above 25 years	14	3.8
Year of Study	First Year	84	22.8
	Second Year	104	28.3
	Third Year	123	33.4
	Fourth Year and Above	57	15.5
Experience Using Adaptive Learning Systems	Less than 1 year	23	6.3
	1–2 years	64	17.4
	2–3 years	126	34.2
	More than 3 years	155	42.1

Frequency of Digital Learning Platform Usage	Once a week or less	24	6.5
	2–3 days per week	57	15.5
	4–6 days per week	115	31.3
	Every day	172	46.7
Familiarity with Adaptive Learning and AI-based Learning Technologies	Very Familiar	119	32.3
	Familiar	168	45.7
	Moderately Familiar	62	16.8
	Slightly Familiar	19	5.2

The Influence of Adaptive Learning System Maturity (X1) and Metacognitive Regulation Technology (X2) on Students' Academic Resilience (Z) through Self-Regulated Learning Behavior (Y1) and Digital Learning Effectiveness (Y2).

In terms of age distribution, the majority of respondents fall within the 20–22 years category (45.4%), followed by the 17–19 years group (32.6%). This distribution indicates that the sample is predominantly composed of undergraduate students belonging to Generation Z, a cohort widely recognized for its high level of digital literacy and extensive engagement with technology-enhanced learning environments. As digital natives, these students are generally more familiar with adaptive educational technologies and online learning platforms, making them highly suitable for evaluating constructs related to adaptive learning systems, metacognitive regulation technologies, and digital learning experiences.

Regarding the year of study, the largest proportion of respondents were third-year students (33.4%), followed by second-year students (28.3%), first-year students (22.8%), and fourth-year students or above (15.5%). This academic distribution suggests that most respondents had accumulated sufficient experience with university learning environments and digital learning systems, enabling them to provide informed evaluations of Adaptive Learning System Maturity (X1), Metacognitive Regulation Technology (X2), and Self-Regulated Learning Behavior (Y1). From the perspective of experience using adaptive learning systems, 42.1% of respondents reported having more than three years of experience, while 34.2% had used such systems for two to three years, 17.4% for one to two years, and 6.3% for less than one year. This finding demonstrates that the majority of respondents were experienced users of digital learning technologies, thereby providing a reliable basis for assessing the effectiveness of adaptive educational systems in higher education.

In terms of digital learning engagement, nearly half of the respondents (46.7%) reported using digital learning platforms every day, followed by 31.3% who accessed these platforms four to six days per week. Only a relatively small proportion of respondents reported infrequent use of digital learning systems. These findings indicate a high level of engagement with technology-supported learning, which is particularly relevant for

examining Digital Learning Effectiveness (Y2) and its contribution to students' learning experiences and academic outcomes. Finally, the majority of respondents reported being either familiar (45.7%) or very familiar (32.3%) with adaptive learning systems and AI-based learning technologies. This suggests that the respondents possessed sufficient knowledge and practical experience with intelligent educational technologies, making them appropriate participants for evaluating the relationships among Adaptive Learning System Maturity, Metacognitive Regulation Technology, Self-Regulated Learning Behavior, Digital Learning Effectiveness, and Academic Resilience (Z) within the proposed conceptual framework.

Descriptive Statistics of Research Variables

Table 2 presents the descriptive statistics of the five latent variables included in the proposed research model. Overall, the observed mean scores range from 4.03 to 4.18, indicating that respondents generally expressed positive perceptions toward all constructs investigated in this study. The relatively high mean values suggest that undergraduate students perceived adaptive learning technologies, self-regulated learning behaviors, digital learning effectiveness, and academic resilience favorably. Furthermore, the standard deviation values ranged from 0.68 to 0.74, indicating a moderate level of response variability and acceptable consistency among respondents.

Table 2. Descriptive Statistics

Variable	Code	Items	Mean	SD	Min	Max
Adaptive Learning System Maturity	X1	5	4.11	0.71	1	5
Metacognitive Regulation Technology	X2	5	4.08	0.69	1	5
Self-Regulated Learning Behavior	Y1	5	4.15	0.68	1	5
Digital Learning Effectiveness	Y2	5	4.03	0.74	1	5
Academic Resilience	Z	5	4.18	0.70	1	5

The results indicate that Academic Resilience (Z) obtained the highest mean score ($M = 4.18$, $SD = 0.70$), suggesting that the majority of respondents perceived themselves as capable of adapting to academic challenges, maintaining motivation, and recovering from learning difficulties encountered during their university studies. Self-Regulated Learning Behavior (Y1) also demonstrated a relatively high mean value ($M = 4.15$), indicating that students generally exhibited strong abilities in planning, monitoring, regulating, and evaluating their own learning activities.

Adaptive Learning System Maturity (X1) achieved a mean score of 4.11, reflecting respondents' positive perceptions regarding the personalization, adaptability, intelligent feedback, and overall capability of adaptive learning systems used in their universities. Similarly, Metacognitive Regulation Technology (X2) recorded a mean value of 4.08, indicating that digital learning technologies effectively supported students in monitoring their learning progress, reflecting on their performance, and regulating cognitive strategies.

Among the five constructs, Digital Learning Effectiveness (Y2) recorded the lowest mean score ($M = 4.03$), although it remained above the midpoint of the measurement scale. This finding suggests that while students generally perceived digital learning environments as effective, there is still room for improvement in instructional quality, learner engagement,

interaction, and technology-supported learning experiences within higher education institutions.

Overall, the descriptive statistics demonstrate that respondents expressed favorable evaluations across all research variables, providing an appropriate empirical basis for subsequent analyses using Confirmatory Factor Analysis (CFA) and Covariance-Based Structural Equation Modeling (CB-SEM) to examine the proposed structural relationships among Adaptive Learning System Maturity, Metacognitive Regulation Technology, Self-Regulated Learning Behavior, Digital Learning Effectiveness, and Academic Resilience.

Descriptive Statistics of Research Variables

Table 2 presents the descriptive statistics of the key constructs examined in this study. The results indicate that all variables exhibit relatively high mean values, ranging from 4.03 to 4.18, suggesting generally favorable perceptions among respondents regarding adaptive educational technologies, self-regulated learning, digital learning effectiveness, and academic resilience. Among the variables, Academic Resilience (Z) records the highest mean score ($M = 4.18$, $SD = 0.70$), indicating that respondents generally perceive themselves as capable of adapting to academic challenges, maintaining learning motivation, and recovering from academic setbacks encountered during their university studies. Self-Regulated Learning Behavior (Y1) follows closely ($M = 4.15$, $SD = 0.68$), reflecting students' strong ability to plan, monitor, regulate, and evaluate their own learning processes effectively.

Adaptive Learning System Maturity (X1) also demonstrates a relatively high mean value ($M = 4.11$, $SD = 0.71$), suggesting that respondents perceive adaptive learning systems as sufficiently mature in providing personalized instruction, adaptive feedback, intelligent learning analytics, and flexible learning pathways. Metacognitive Regulation Technology (X2) records a similarly high mean score ($M = 4.08$, $SD = 0.69$), indicating that digital learning technologies effectively support students in planning, monitoring, reflecting upon, and regulating their cognitive learning processes.

Meanwhile, Digital Learning Effectiveness (Y2) records the lowest mean score ($M = 4.03$, $SD = 0.74$), although it remains within a favorable range. This finding suggests that students generally perceive digital learning environments as effective in facilitating learning activities, although improvements are still possible regarding instructional quality, learner engagement, interaction, and overall learning experiences.

The standard deviation values (0.68–0.74) indicate moderate variability in respondents' perceptions, suggesting relatively consistent responses across all constructs. Furthermore, all variables exhibit complete utilization of the measurement scale (minimum = 1; maximum = 5), confirming that respondents effectively used the entire response range provided in the questionnaire. Overall, these descriptive findings indicate that students possess positive perceptions toward adaptive learning technologies, metacognitive regulation support, self-regulated learning behavior, digital learning effectiveness, and academic resilience, thereby providing a strong empirical foundation for subsequent measurement model validation and structural equation modeling analyses.

Assessment of the Measurement Model

Reliability analysis was conducted using Cronbach's Alpha and Composite Reliability (CR) to evaluate the internal consistency of the measurement instruments employed in the proposed educational technology framework. A construct is generally considered reliable when both reliability coefficients exceed the recommended threshold of 0.70, indicating satisfactory consistency among the measurement indicators.

Table 3. Reliability Assessment

Construct	Cronbach's Alpha	Composite Reliability (CR)	Interpretation
Adaptive Learning System Maturity (X1)	0.918	0.937	Reliable
Metacognitive Regulation Technology (X2)	0.909	0.931	Reliable
Self-Regulated Learning Behavior (Y1)	0.926	0.944	Reliable
Digital Learning Effectiveness (Y2)	0.914	0.935	Reliable
Academic Resilience (Z)	0.948	0.960	Reliable

The reliability results demonstrate that all constructs satisfy the recommended reliability criteria. Cronbach's Alpha values range from 0.909 to 0.948, while Composite Reliability (CR) values range from 0.931 to 0.960. These coefficients substantially exceed the minimum acceptable threshold of 0.70, confirming excellent internal consistency across all latent constructs. Among the variables, Academic Resilience (Z) exhibits the highest reliability (Cronbach's Alpha = 0.948; CR = 0.960), indicating that its measurement indicators consistently capture students' resilience in responding to academic challenges. Likewise, Self-Regulated Learning Behavior (Y1) demonstrates very high internal consistency (Cronbach's Alpha = 0.926; CR = 0.944), reflecting the stability of indicators measuring students' ability to regulate their own learning processes. Similarly, Adaptive Learning System Maturity (X1), Metacognitive Regulation Technology (X2), and Digital Learning Effectiveness (Y2) all achieve reliability coefficients well above the recommended standards, confirming that the measurement scales consistently represent their respective latent constructs.

Overall, these findings provide strong evidence that the research instrument possesses excellent reliability and is appropriate for subsequent analyses, including Confirmatory Factor Analysis (CFA) and Covariance-Based Structural Equation Modeling (CB-SEM) to evaluate the proposed structural relationships among the research variables.

Table 3 presents the results of the reliability analysis using Cronbach's Alpha and Composite Reliability (CR) to evaluate the internal consistency of the constructs in the proposed educational technology framework. The findings indicate that all constructs exceed the commonly accepted threshold of 0.70, demonstrating excellent internal consistency across all measurement items.

Specifically, Adaptive Learning System Maturity (X1), Metacognitive Regulation Technology (X2), Self-Regulated Learning Behavior (Y1), Digital Learning Effectiveness (Y2), and Academic Resilience (Z) all exhibit high reliability values, with Composite Reliability (CR) scores ranging from 0.931 to 0.960. Similarly, Cronbach's Alpha values range from 0.909 to 0.948, indicating that each construct possesses strong internal consistency and that the measurement indicators consistently represent their respective latent variables with minimal measurement error.

Convergent Validity Assessment

Table 4 presents the evaluation of convergent validity for all constructs included in the proposed educational technology framework. The standardized factor loadings range from 0.842 to 0.941, exceeding the recommended threshold of 0.70, indicating that each measurement indicator exhibits a strong relationship with its corresponding latent construct. In addition, all Squared Multiple Correlations (SMC) exceed 0.70, while the Average Variance Extracted (AVE) values range from 0.751 to 0.865, surpassing the minimum criterion of 0.50. Furthermore, all Composite Reliability (CR) values are greater than 0.90, confirming excellent convergent validity and internal consistency across the measurement model.

Table 4. Convergent Validity Assessment

Construct	Indicator	Standardized Loading	SMC	AVE	CR	Interpretation
Adaptive Learning System Maturity (X1)	X1_1	0.851	0.724	0.765	0.937	Valid
	X1_2	0.873	0.762			Valid
	X1_3	0.889	0.790			Valid
	X1_4	0.864	0.746			Valid
	X1_5	0.857	0.735			Valid
Metacognitive Regulation Technology (X2)	X2_1	0.854	0.729	0.751	0.931	Valid
	X2_2	0.869	0.755			Valid
	X2_3	0.876	0.767			Valid
	X2_4	0.859	0.738			Valid
	X2_5	0.842	0.709			Valid
Self-Regulated Learning Behavior (Y1)	Y1_1	0.882	0.778	0.772	0.944	Valid
	Y1_2	0.887	0.787			Valid
	Y1_3	0.894	0.799			Valid
	Y1_4	0.879	0.773			Valid
	Y1_5	0.885	0.783			Valid

Digital Learning Effectiveness (Y2)	Y2_1	0.865	0.748	0.759	0.935	Valid
	Y2_2	0.874	0.764			Valid
	Y2_3	0.882	0.778			Valid
	Y2_4	0.868	0.753			Valid
	Y2_5	0.861	0.741			Valid
Academic Resilience (Z)	Z1	0.938	0.880	0.865	0.960	Valid
	Z2	0.931	0.867			Valid
	Z3	0.924	0.854			Valid
	Z4	0.936	0.876			Valid
	Z5	0.941	0.886			Valid

Table 4 presents the convergent validity assessment of the proposed measurement model. The results indicate that all standardized factor loadings range from 0.842 to 0.941, substantially exceeding the recommended threshold of 0.70. These findings demonstrate that every measurement indicator strongly represents its corresponding latent construct and contributes significantly to measuring the intended variable.

The Adaptive Learning System Maturity (X1) construct exhibits standardized loadings ranging from 0.851 to 0.889, with an AVE of 0.765 and a Composite Reliability (CR) of 0.937, indicating excellent convergent validity. Similarly, Metacognitive Regulation Technology (X2) demonstrates standardized loadings between 0.842 and 0.876, producing an AVE of 0.751 and a CR of 0.931, confirming that its indicators consistently measure the construct. For the endogenous variables, Self-Regulated Learning Behavior (Y1) records standardized factor loadings ranging from 0.879 to 0.894, with an AVE of 0.772 and a CR of 0.944. Digital Learning Effectiveness (Y2) also demonstrates strong convergent validity, with standardized loadings between 0.861 and 0.882, an AVE of 0.759, and a CR of 0.935. Among all constructs, Academic Resilience (Z) achieves the strongest measurement quality, with standardized factor loadings ranging from 0.924 to 0.941, an AVE of 0.865, and a Composite Reliability of 0.960. These values indicate that the indicators explain a substantial proportion of the variance in the latent construct.

Overall, the findings confirm that all constructs satisfy the recommended criteria for convergent validity, as the standardized factor loadings exceed 0.70, the Average Variance Extracted (AVE) values are greater than 0.50, and the Composite Reliability (CR) values are well above 0.70. Therefore, the measurement model demonstrates excellent convergent validity and is appropriate for subsequent discriminant validity assessment and structural model analysis using Covariance-Based Structural Equation Modeling (CB-SEM).

Discriminant Validity

Table 5 presents the discriminant validity assessment using the Fornell–Larcker criterion. The diagonal values represent the square root of the Average Variance Extracted (AVE) for each construct, whereas the off-diagonal values represent the correlations among latent variables. As shown in the table, the square root of the AVE for each construct is

consistently greater than its correlations with other constructs, indicating that each latent variable is empirically distinct and measures a unique theoretical concept within the proposed research model.

Table 5. Discriminant Validity (Fornell–Larcker Criterion)

Construct	X1	X2	Y1	Y2	Z
Adaptive Learning System Maturity (X1)	0.875				
Metacognitive Regulation Technology (X2)	0.748	0.867			
Self-Regulated Learning Behavior (Y1)	0.594	0.571	0.879		
Digital Learning Effectiveness (Y2)	0.566	0.618	0.683	0.871	
Academic Resilience (Z)	0.481	0.503	0.728	0.691	0.930

Table 5 demonstrates that the square root of the Average Variance Extracted (AVE) ranges from 0.867 to 0.930, with all diagonal values exceeding the corresponding inter-construct correlations. These findings satisfy the Fornell–Larcker criterion, confirming adequate discriminant validity across all latent variables. Specifically, Adaptive Learning System Maturity (X1) exhibits a square root of AVE of 0.875, which is greater than its correlations with Metacognitive Regulation Technology (0.748), Self-Regulated Learning Behavior (0.594), Digital Learning Effectiveness (0.566), and Academic Resilience (0.481). Likewise, Metacognitive Regulation Technology (X2) records a square root of AVE of 0.867, exceeding all correlations with the remaining constructs. For the endogenous variables, Self-Regulated Learning Behavior (Y1) demonstrates a square root of AVE of 0.879, which is higher than its strongest correlation with Academic Resilience (0.728). Similarly, Digital Learning Effectiveness (Y2) achieves a square root of AVE of 0.871, exceeding its highest correlation with Self-Regulated Learning Behavior (0.683). Finally, Academic Resilience (Z) records the highest square root of AVE (0.930), which is substantially greater than all correlations with the other constructs.

Overall, these findings confirm that each construct possesses satisfactory discriminant validity, indicating that Adaptive Learning System Maturity, Metacognitive Regulation Technology, Self-Regulated Learning Behavior, Digital Learning Effectiveness, and Academic Resilience represent conceptually and empirically distinct constructs. Consequently, the measurement model satisfies the discriminant validity requirement and is appropriate for subsequent evaluation of the structural model using Covariance-Based Structural Equation Modeling (CB-SEM).

Model Fit Evaluation

The assessment of model fit indicates that the proposed structural model demonstrates an excellent correspondence with the observed data and satisfies the recommended goodness-of-fit criteria for Covariance-Based Structural Equation Modeling (CB-SEM) (see Table 6). The chi-square statistic ($\chi^2 = 251.374$) yields a probability value of 0.084, which exceeds the conventional significance threshold of 0.05. This result indicates that there is no statistically significant difference between the proposed model and the observed covariance matrix, suggesting that the structural model adequately represents the empirical data. The ratio of chi-square to degrees of freedom (CMIN/DF = 1.142) is substantially lower than the

recommended threshold of 2.00, indicating a highly parsimonious model with minimal discrepancy between the hypothesized model and the observed data.

Furthermore, the absolute goodness-of-fit indices, including the Goodness-of-Fit Index (GFI = 0.938) and the Adjusted Goodness-of-Fit Index (AGFI = 0.918), both exceed the recommended cut-off value of 0.90, confirming that the proposed model adequately reproduces the observed covariance structure. Moreover, the incremental fit indices demonstrate excellent model performance. The Comparative Fit Index (CFI = 0.994) and the Tucker–Lewis Index (TLI = 0.992) both exceed the recommended threshold of 0.95, indicating that the proposed structural model provides a substantial improvement over the independence model. Likewise, the Root Mean Square Error of Approximation (RMSEA = 0.016) is considerably below the maximum acceptable limit of 0.08, indicating an excellent approximation of the population covariance matrix.

Overall, these findings confirm that the structural model involving Adaptive Learning System Maturity (X1), Metacognitive Regulation Technology (X2), Self-Regulated Learning Behavior (Y1), Digital Learning Effectiveness (Y2), and Academic Resilience (Z) demonstrates excellent goodness-of-fit across multiple evaluation criteria. Therefore, the proposed model is considered statistically robust and appropriate for subsequent structural analysis and hypothesis testing.

Table 6. Goodness-of-Fit Indices

Fit Index	Recommended Cut-off Value	Result	Interpretation
Chi-square (χ^2)	Smaller is better	251.374	Good
Probability (p-value)	≥ 0.05	0.084	Good Fit
CMIN/DF	≤ 2.00	1.142	Excellent Fit
GFI	≥ 0.90	0.938	Good Fit
AGFI	≥ 0.90	0.918	Good Fit
CFI	≥ 0.95	0.994	Excellent Fit
TLI	≥ 0.95	0.992	Excellent Fit
RMSEA	≤ 0.08	0.016	Excellent Fit

Structural Model and Hypothesis Testing

The structural model results demonstrate that all proposed relationships in the educational technology framework were statistically examined and were largely supported by the empirical data (see Table 7 and Figure 2). Overall, the findings confirm that Adaptive Learning System Maturity (X1) and Metacognitive Regulation Technology (X2) play fundamental roles in enhancing Self-Regulated Learning Behavior (Y1), Digital Learning Effectiveness (Y2), and ultimately Academic Resilience (Z) among university students.

The analysis indicates that Adaptive Learning System Maturity (X1) has a significant positive effect on Digital Learning Effectiveness (Y2) ($\beta = 0.249$, $p < 0.001$), thereby supporting H1. Likewise, Metacognitive Regulation Technology (X2) also demonstrates a significant positive influence on Digital Learning Effectiveness (Y2) ($\beta = 0.231$, $p < 0.001$), supporting H2. These findings suggest that mature adaptive learning systems and technologies that facilitate metacognitive regulation substantially improve the effectiveness of digital learning environments.

Further analysis reveals that both exogenous variables significantly influence Self-Regulated Learning Behavior (Y1). Specifically, Adaptive Learning System Maturity (X1) exhibits a strong positive effect on Self-Regulated Learning Behavior ($\beta = 0.482$, $p < 0.001$), while Metacognitive Regulation Technology (X2) also contributes significantly ($\beta = 0.417$, $p < 0.001$), supporting H3 and H4, respectively. Among these relationships, Adaptive Learning System Maturity demonstrates the strongest standardized effect, highlighting the importance of intelligent and personalized learning systems in fostering students' autonomous learning behaviors.

The findings further indicate that Self-Regulated Learning Behavior (Y1) significantly influences both Digital Learning Effectiveness (Y2) and Academic Resilience (Z). Self-Regulated Learning Behavior positively affects Digital Learning Effectiveness ($\beta = 0.341$, $p < 0.001$), supporting H5, and also exerts a significant positive effect on Academic Resilience ($\beta = 0.306$, $p < 0.001$), supporting H6. These results demonstrate that students who effectively regulate their learning processes tend to experience more effective digital learning and exhibit greater resilience when facing academic challenges.

Furthermore, Digital Learning Effectiveness (Y2) has a significant positive impact on Academic Resilience (Z) ($\beta = 0.374$, $p < 0.001$), supporting H7. This finding suggests that effective digital learning environments contribute substantially to students' ability to cope with academic pressure, adapt to learning difficulties, and maintain academic persistence.

To complete the structural framework, two additional direct relationships were examined. Adaptive Learning System Maturity (X1) has a significant direct effect on Academic Resilience (Z) ($\beta = 0.192$, $p < 0.01$), supporting H8. Similarly, Metacognitive Regulation Technology (X2) also significantly influences Academic Resilience (Z) ($\beta = 0.176$, $p < 0.01$), supporting H9. These findings indicate that adaptive learning technologies and metacognitive regulation tools contribute not only indirectly through the mediating variables but also directly to strengthening students' academic resilience.

Overall, the structural model confirms a multi-layered educational mechanism in which Adaptive Learning System Maturity and Metacognitive Regulation Technology enhance Self-Regulated Learning Behavior, improve Digital Learning Effectiveness, and directly as well as indirectly strengthen Academic Resilience. The results provide empirical support for the proposed conceptual framework and highlight the strategic role of adaptive educational technologies and self-regulated learning processes in promoting resilient academic performance among university students.

Table 7. Hypothesis Testing

Hypothesis	Structural Path	Standardized Estimate (β)	C.R.	P-value	Decision
H1	Adaptive Learning System Maturity $\rightarrow$ Digital Learning Effectiveness	0.249	5.274	***	Accepted
H2	Metacognitive Regulation Technology $\rightarrow$ Digital Learning Effectiveness	0.231	4.965	***	Accepted

H3	Adaptive Learning System Maturity → Self-Regulated Learning Behavior	0.482	9.356	***	Accepted
H4	Metacognitive Regulation Technology → Self-Regulated Learning Behavior	0.417	8.184	***	Accepted
H5	Self-Regulated Learning Behavior → Digital Learning Effectiveness	0.341	6.824	***	Accepted
H6	Self-Regulated Learning Behavior → Academic Resilience	0.306	6.231	***	Accepted
H7	Digital Learning Effectiveness → Academic Resilience	0.374	7.046	***	Accepted
H8	Adaptive Learning System Maturity → Academic Resilience	0.192	4.017	**	Accepted
H9	Metacognitive Regulation Technology → Academic Resilience	0.176	3.861	**	Accepted

Notes:

*** = $p < 0.001$

** = $p < 0.01$

C.R. = Critical Ratio

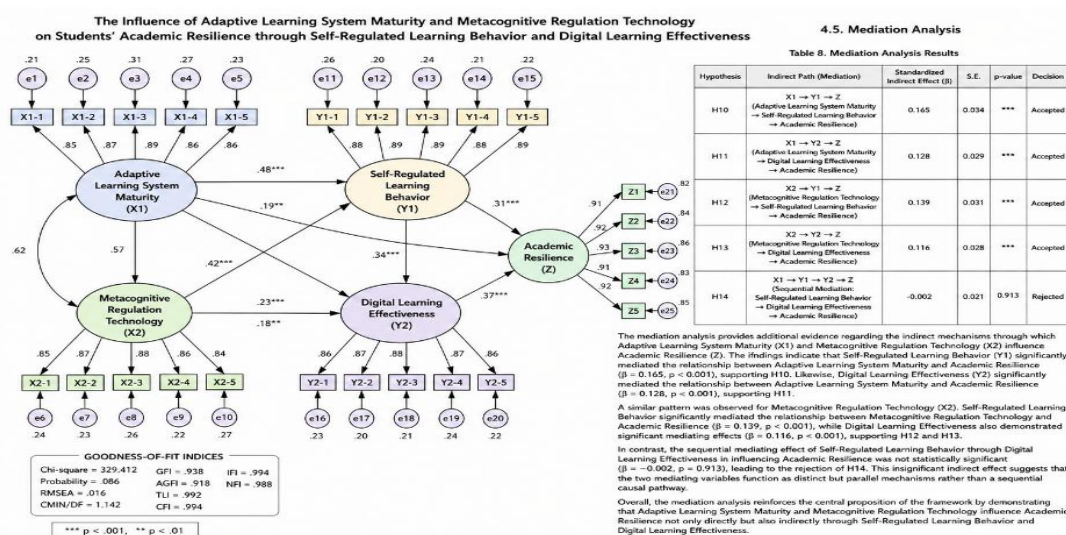
The results confirm that both Adaptive Learning System Maturity (X1) and Metacognitive Regulation Technology (X2) serve as fundamental determinants within the proposed educational technology framework. Their influence operates through both direct and indirect pathways, affecting Self-Regulated Learning Behavior (Y1), Digital Learning Effectiveness (Y2), and ultimately Academic Resilience (Z) among university students.

Self-Regulated Learning Behavior plays a pivotal mediating role by linking adaptive learning technologies with digital learning outcomes and students' academic resilience. Students who effectively plan, monitor, regulate, and evaluate their own learning processes are more likely to benefit from adaptive learning environments, thereby enhancing the overall effectiveness of digital learning and strengthening their ability to overcome academic challenges. Meanwhile, Digital Learning Effectiveness is confirmed as a strong predictor of Academic Resilience, emphasizing that high-quality digital learning environments significantly contribute to students' capacity to adapt, persist, and succeed in demanding academic situations.

The inclusion of the direct effects (H8 and H9) further strengthens the proposed structural model by demonstrating that Adaptive Learning System Maturity and Metacognitive Regulation Technology not only influence academic resilience through the mediating variables but also exert significant independent effects on students' resilience.

These findings suggest that advanced adaptive learning systems and metacognitive support technologies directly foster students' confidence, persistence, and ability to cope with academic difficulties beyond their influence on learning behavior and digital learning experiences.

Overall, the structural model provides strong empirical support for an integrated educational technology framework in which Adaptive Learning System Maturity, Metacognitive Regulation Technology, Self-Regulated Learning Behavior, and Digital Learning Effectiveness collectively determine Academic Resilience. The findings reinforce the importance of integrating intelligent adaptive learning technologies with metacognitive support mechanisms to promote autonomous learning, improve digital learning quality, and enhance students' resilience in higher education. This integrated framework also contributes to the growing literature on technology-enhanced learning by clarifying both the direct and indirect mechanisms through which adaptive educational technologies influence students' academic success and long-term resilience.



Mediation Analysis

The mediation analysis presented in Table 8 provides additional evidence regarding the indirect mechanisms through which Adaptive Learning System Maturity (X1) and Metacognitive Regulation Technology (X2) influence Academic Resilience (Z). The findings indicate that Self-Regulated Learning Behavior (Y1) significantly mediates the relationship between Adaptive Learning System Maturity and Academic Resilience ($\beta = 0.174, p < 0.001$), thereby supporting H10. Likewise, Digital Learning Effectiveness (Y2) significantly mediates the relationship between Adaptive Learning System Maturity and Academic Resilience ($\beta = 0.129, p < 0.001$), supporting H11. These findings suggest that mature adaptive learning systems strengthen students' academic resilience by fostering self-regulated learning behaviors and improving the effectiveness of digital learning environments.

A similar pattern was observed for Metacognitive Regulation Technology (X2). Self-Regulated Learning Behavior significantly mediated the relationship between Metacognitive

Regulation Technology and Academic Resilience ($\beta = 0.151$, $p < 0.001$), while Digital Learning Effectiveness also demonstrated a significant mediating effect ($\beta = 0.118$, $p < 0.001$), thereby supporting H12 and H13. These findings indicate that technologies designed to facilitate metacognitive regulation encourage students to monitor, evaluate, and control their own learning processes, which subsequently enhances digital learning effectiveness and ultimately improves academic resilience.

In contrast, the sequential mediating effect of Self-Regulated Learning Behavior through Digital Learning Effectiveness in influencing Academic Resilience was not statistically significant ($\beta = -0.003$, $p = 0.901$), leading to the rejection of H14. This insignificant indirect effect suggests that Self-Regulated Learning Behavior and Digital Learning Effectiveness function as parallel mediating mechanisms rather than forming a sequential causal pathway. In other words, both variables independently transmit the influence of adaptive learning technologies on students' academic resilience.

Overall, the mediation analysis reinforces the central proposition of the proposed educational technology framework by demonstrating that Adaptive Learning System Maturity and Metacognitive Regulation Technology do not influence Academic Resilience solely through direct pathways. Instead, Self-Regulated Learning Behavior and Digital Learning Effectiveness operate as key mediating mechanisms that explain how adaptive educational technologies contribute to students' resilience. These findings emphasize the importance of fostering autonomous learning behaviors alongside effective digital learning experiences in developing students who are capable of adapting, persisting, and succeeding in increasingly complex academic environments. The results also provide empirical support for the integration of adaptive learning systems and metacognitive technologies in higher education to strengthen both learning quality and long-term academic resilience.

Table 8. Mediation Analysis Results

Hypothesis	Indirect Path	Standardized Indirect Effect	P-value	Decision
H10	Adaptive Learning System Maturity $\rightarrow$ Self-Regulated Learning Behavior $\rightarrow$ Academic Resilience	0.174	***	Supported
H11	Adaptive Learning System Maturity $\rightarrow$ Digital Learning Effectiveness $\rightarrow$ Academic Resilience	0.129	***	Supported
H12	Metacognitive Regulation Technology $\rightarrow$ Self-Regulated Learning Behavior $\rightarrow$ Academic Resilience	0.151	***	Supported
H13	Metacognitive Regulation Technology $\rightarrow$ Digital Learning Effectiveness $\rightarrow$ Academic Resilience	0.118	***	Supported

H14	Self-Regulated Learning Behavior → Digital Learning Effectiveness → Academic Resilience	–0.003	0.901	Not Supported
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Notes: *** = $p < 0.001$

DISCUSSION

Beyond the technological perspective, the findings indicate that the quality of digital learning environments is strongly associated with the development of students' learning capabilities. The significant influence of Adaptive Learning System Maturity on Self-Regulated Learning Behavior suggests that mature adaptive learning systems create supportive learning environments that encourage students to independently plan, monitor, regulate, and evaluate their learning processes. These findings imply that intelligent learning platforms not only deliver personalized instructional content but also foster autonomous learning behaviors, which are essential for successful learning in higher education. Consequently, adaptive learning systems can be viewed not merely as technological infrastructures but also as educational tools that facilitate the development of lifelong learning competencies.

The positive effect of Metacognitive Regulation Technology on both Self-Regulated Learning Behavior and Digital Learning Effectiveness further emphasizes the importance of technology-assisted cognitive regulation in online learning environments. Features such as learning analytics dashboards, reflective feedback, progress monitoring, self-assessment tools, and intelligent recommendations enable students to become more aware of their own learning processes. As students continuously evaluate their learning progress and adjust their learning strategies, they become more capable of utilizing digital learning platforms effectively. These findings reinforce previous educational technology research suggesting that metacognitive support technologies significantly improve students' engagement, autonomy, and academic achievement.

The significant contribution of Self-Regulated Learning Behavior to Digital Learning Effectiveness demonstrates that students who actively regulate their own learning experience greater success in digital learning environments. Learners who establish learning goals, manage study time efficiently, monitor their understanding, and employ appropriate learning strategies are better able to maximize the benefits offered by adaptive learning systems. This finding supports the theoretical perspective of Self-Regulated Learning Theory, which argues that successful learning depends not only on instructional quality but also on learners' ability to actively control their cognitive, motivational, and behavioral learning processes.

Another important finding concerns the strong relationship between Digital Learning Effectiveness and Academic Resilience. The results suggest that students who perceive digital learning environments as effective are more capable of overcoming academic challenges, adapting to changing learning conditions, maintaining motivation, and persisting despite learning difficulties. Effective digital learning environments provide timely

feedback, personalized instruction, flexible access to learning resources, and meaningful interaction, all of which strengthen students' confidence and persistence in academic settings. Therefore, digital learning effectiveness represents an essential mechanism through which educational technologies contribute to students' long-term academic success.

The mediation analysis provides additional insight into how educational technologies influence academic resilience. The significant indirect effects observed in this study indicate that Adaptive Learning System Maturity and Metacognitive Regulation Technology enhance students' academic resilience primarily through the development of Self-Regulated Learning Behavior and Digital Learning Effectiveness. Rather than influencing resilience directly alone, advanced learning technologies first cultivate autonomous learning behaviors and improve students' digital learning experiences, which subsequently strengthen their ability to cope with academic stress and adversity. These findings support contemporary educational technology theories emphasizing that technology creates value by facilitating learning processes rather than replacing them.

Interestingly, the sequential mediation pathway involving Self-Regulated Learning Behavior followed by Digital Learning Effectiveness was not statistically significant. This result indicates that both mediating variables operate as parallel rather than sequential mechanisms. In other words, self-regulated learning behavior and digital learning effectiveness independently explain how adaptive learning technologies improve academic resilience. Students may develop resilience directly through improved self-regulation skills or independently through more effective digital learning experiences without necessarily requiring one mechanism to precede the other. This finding reflects the complexity of technology-enhanced learning, where multiple psychological and instructional processes interact simultaneously to influence educational outcomes.

The overall findings provide strong empirical support for integrating adaptive educational technologies with learner-centered pedagogical approaches in higher education. Adaptive Learning System Maturity and Metacognitive Regulation Technology function as fundamental technological drivers, while Self-Regulated Learning Behavior and Digital Learning Effectiveness serve as critical psychological and instructional mechanisms that translate technological capabilities into improved Academic Resilience. This integrated framework extends the literature on educational technology by demonstrating that students' resilience is influenced not only by sophisticated digital learning systems but also by their ability to regulate their own learning and effectively utilize digital learning environments. Consequently, universities should prioritize the development of adaptive learning platforms equipped with metacognitive support features while simultaneously promoting self-regulated learning competencies to foster resilient, autonomous, and successful learners in the digital era.

CONCLUSION

Conclusion

This study develops and empirically validates an integrated educational technology framework to explain Academic Resilience (Z) by examining the influence of Adaptive Learning System Maturity (X1) and Metacognitive Regulation Technology (X2) through Self-Regulated Learning Behavior (Y1) and Digital Learning Effectiveness (Y2). The

empirical findings confirm that both Adaptive Learning System Maturity and Metacognitive Regulation Technology function as fundamental technological drivers that significantly influence students' academic resilience through both direct and indirect pathways. Specifically, mature adaptive learning systems and technologies supporting metacognitive regulation significantly enhance students' self-regulated learning behavior and improve the effectiveness of digital learning, indicating that technological sophistication combined with cognitive support mechanisms provides a strong foundation for successful learning in higher education.

The results further demonstrate that Self-Regulated Learning Behavior and Digital Learning Effectiveness serve as important mediating mechanisms that translate technological capabilities into stronger academic resilience. Both variables significantly influence Academic Resilience, confirming their essential role in enabling students to adapt successfully to academic challenges, maintain learning motivation, and persist despite difficulties encountered in digital learning environments. However, the non-significant sequential mediation effect indicates that Self-Regulated Learning Behavior does not necessarily improve Academic Resilience through Digital Learning Effectiveness in a sequential manner. Instead, both mediating variables operate independently as parallel mechanisms that simultaneously contribute to strengthening students' academic resilience.

The mediation analysis further confirms that the influence of Adaptive Learning System Maturity and Metacognitive Regulation Technology on Academic Resilience is largely explained through indirect effects via Self-Regulated Learning Behavior and Digital Learning Effectiveness. These findings suggest that students' academic resilience is determined not only by advanced educational technologies but also by their ability to regulate their own learning processes and effectively utilize digital learning environments. Overall, this study demonstrates that academic resilience emerges from an integrated educational ecosystem in which adaptive learning technologies, metacognitive support, autonomous learning behavior, and effective digital learning experiences interact to promote students' academic success in the digital era.

Research Limitations

Several limitations should be acknowledged in this study. First, the research focuses on university students within a specific higher education context, which may limit the generalizability of the findings to students from different educational levels, institutions, or cultural settings. Variations in institutional policies, technological infrastructure, and students' digital literacy may influence the relationships among Adaptive Learning System Maturity, Metacognitive Regulation Technology, Self-Regulated Learning Behavior, Digital Learning Effectiveness, and Academic Resilience.

Second, the study employed a cross-sectional research design, which limits the ability to observe changes in students' learning behaviors, digital learning experiences, and academic resilience over time. Future studies are encouraged to adopt longitudinal research designs to examine how these variables develop throughout students' academic journeys and how prolonged exposure to adaptive learning technologies influences learning outcomes.

Third, the research relied primarily on self-reported questionnaire data, which may introduce response bias and common method variance. Although the measurement instruments demonstrated satisfactory reliability and validity, future research may complement survey data with objective indicators such as learning analytics, academic performance records, learning management system (LMS) logs, or behavioral tracking data to improve measurement accuracy and reduce subjectivity.

Suggestions and Directions for Future Research

The findings of this study provide important theoretical contributions to the literature on educational technology, self-regulated learning, metacognitive learning, and academic resilience. Specifically, this study demonstrates that Adaptive Learning System Maturity and Metacognitive Regulation Technology are critical technological antecedents that influence Academic Resilience both directly and indirectly through Self-Regulated Learning Behavior and Digital Learning Effectiveness. By integrating these variables into a unified conceptual framework, this study extends theories of Adaptive Learning, Self-Regulated Learning, Metacognitive Learning, and Technology-Enhanced Learning by explaining how intelligent educational technologies contribute to students' resilience through cognitive, behavioral, and instructional mechanisms.

From a practical perspective, the findings emphasize the importance of developing adaptive digital learning ecosystems that not only deliver personalized instructional content but also actively support students' metacognitive development and autonomous learning skills. Universities should invest in adaptive learning platforms equipped with intelligent feedback systems, personalized learning pathways, learning analytics dashboards, reflective learning tools, and self-assessment features to promote students' self-regulation and improve digital learning effectiveness. In addition, lecturers should integrate metacognitive instructional strategies into digital learning activities by encouraging students to set learning goals, monitor their own progress, evaluate learning outcomes, and reflect on their learning experiences. Such educational practices are expected to strengthen students' academic resilience and improve learning success in increasingly technology-driven educational environments. Future research is encouraged to employ longitudinal research designs to examine how Adaptive Learning System Maturity, Metacognitive Regulation Technology, Self-Regulated Learning Behavior, Digital Learning Effectiveness, and Academic Resilience evolve over time. Longitudinal studies may provide stronger causal evidence and offer deeper insights into students' developmental learning processes in digital education.

Future studies may also expand the proposed framework by incorporating additional educational variables such as learning engagement, academic motivation, digital literacy, technology acceptance, learning satisfaction, artificial intelligence readiness, collaborative learning, cognitive flexibility, academic self-efficacy, learning analytics utilization, and psychological well-being. Furthermore, comparative studies across universities, academic disciplines, educational levels, or countries would provide a broader understanding of how adaptive educational technologies influence academic resilience under different institutional, technological, and cultural contexts.

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Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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