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Research Article

From emotional intelligence and digital mindset to academic achievement: The mediating role of self-regulated learning and the moderating effects of technology acceptance and digital resilience

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This study aims to examine the effects of emotional intelligence and digital mindset on students' achievement in technology-based economics learning, with self-regulated learning as a mediating variable, and technology acceptance and digital resilience as moderating variables. An ex post facto quantitative design was employed in the study. Data were obtained through a structured survey administered to 392 students from public senior high schools. The findings reveal that both emotional intelligence and digital mindset significantly enhance self-regulated learning, while digital mindset also directly contributes to academic achievement. Furthermore, self-regulated learning has a significant positive effect on achievement and mediates the influence of both emotional intelligence and digital mindset on learning outcomes in technology-supported economics classes. In contrast, neither technology acceptance nor digital resilience demonstrates a significant moderating role in the model. These results highlight self-regulated learning as a key mechanism linking psychosocial factors and digital dispositions to students' academic achievement. In conclusion, success in technology-based economics learning is influenced more by emotional intelligence, digital mindset, and self-regulated learning than by technology acceptance or digital resilience. The proposed moderated–mediation model contributes to digital learning research and offers practical implications for educational practice.

Keywords: Digital mindset; Digital resilience; Emotional intelligence; Self-regulated learning; Student achievement; Technology acceptance

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1. Introduction

The rapid advancement of information and communication technologies has brought about significant transformations in formal education, including the teaching of economics at the senior high school level. The Indonesian government, through the Merdeka Curriculum and the *Merdeka Mengajar* platform, has strongly encouraged the integration of digital technologies in schools. In practice, many Indonesian senior high schools have adopted technology-supported learning

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environments through learning management systems [LMS], Google Classroom, and other e-learning applications. Despite the availability of relatively adequate infrastructure, the successful implementation of technology-based learning often faces non-technical barriers such as instructional design, teachers' pedagogical readiness, and students' preparedness to engage in digital learning environments (Pasipamire et al., 2025; Solekhah et al., 2025; Sui et al., 2023).

Preliminary classroom observations and interviews with economics teachers in several public high schools in Padang, West Sumatra, revealed that some students still struggle with time management, are easily distracted by social media during online learning, and lack initiative for independent study. This phenomenon illustrates that the mere availability of infrastructure does not automatically guarantee effective digital learning without sufficient attention to psychosocial factors and students' learning skills (Chen, 2025; Mustofa et al., 2022). Consequently, focusing on students' internal attributes becomes crucial in explaining variations in achievement within technology-enhanced economics learning.

Based on data from Statistics Indonesia (Badan Pusat Statistik [BPS]) and the Center for Educational Assessment (Pusmendik) of the Ministry of Education, Culture, Research, and Technology (Kemendikbudristek) Indonesia, the academic achievement of senior high school students in Indonesia still shows significant disparities across regions and subjects. The results of the 2023 Computer-Based National Assessment [ANBK] released by Pusmendik revealed that the literacy and numeracy performance of senior high school students in West Sumatra Province were slightly above the national average, with literacy and numeracy scores of 54.32 and 52.76, respectively, on a 100-point scale. However, students' mastery of economic concepts remains relatively low compared to other subjects. This finding is consistent with the 2024 BPS report on the Secondary Education Achievement Index in West Sumatra, which recorded a score of 74.11, indicating that improvement is still needed to enhance students' readiness for national examinations, university entrance tests [UTBK], and competency-based learning in economics.

A growing body of research highlights the crucial role of Emotional Intelligence [EI] in helping students manage academic stress, sustain motivation, and maintain productive social relationships, which in turn fosters learning engagement and academic success (Kuswanto et al., 2023; Shengyao, 2024). Based on Self-Determination Theory (Deci & Ryan, 2000), individuals with higher emotional intelligence are better able to fulfill their basic psychological needs for autonomy, competence, and relatedness, which form the foundation of self-regulation and intrinsic motivation in learning. Accordingly, EI functions as an affective resource that enables students to develop more effective self-regulation.

In addition, digital mindset [DM] which encompasses openness to new technologies, adaptive learning ability, digital creativity, online collaboration, and data-driven problem-solving—has been identified as an important predictor of how students utilize digital tools for learning and develop self-directed learning strategies (Meng et al., 2024; Solekhah et al., 2025). According to Social Cognitive Theory (Bandura, 1986), a digital mindset can be viewed as a form of self-efficacy and outcome expectancy in digital contexts, influencing how learners interpret, process, and employ technology to regulate their learning behaviors. The operational definition of DM in this study refers to a positive orientation toward technology, openness to digital change, and the ability to integrate digital tools effectively into learning strategies (Leonardi, 2022).

The concept of self-regulated learning [SRL] serves as the central mechanism through which dispositions such as EI and DM are translated into effective learning practices including planning, monitoring, regulation of cognitive and motivational strategies, and reflection on learning outcomes (Pintrich, 2004; Tinajero et al., 2024; Zimmerman, 2000). Grounded in Social Cognitive Theory, SRL results from the interaction among personal factors (emotions, beliefs, mindsets), behaviors, and learning environments (Zimmerman, 2000). Thus, SRL is not merely a skill but a metacognitive process linking emotional capacity and technological attitudes to academic outcomes, as evidenced by recent mediation studies in technology-supported learning contexts (Chen et al., 2025). Recent studies show that technology-enriched learning environments can enhance SRL when supported by adequate digital literacy and appropriate instructional contexts (Arianto & Hanif, 2024; Faza & Lestari, 2025; Sui et al., 2024). Therefore, positioning SRL as a mediator in this model is both a theoretical and practical decision aligned with the principle of triadic reciprocity in Social Cognitive Theory.

Meanwhile, technology acceptance [TA] and digital resilience [DR] emerge as contextual variables that potentially moderate the effects of psychosocial factors on learning outcomes. According to the technology acceptance model [TAM] developed by Davis (1989), perceived usefulness and perceived ease of use determine an individual's level of acceptance and utilization of technology. In educational contexts, students with higher TA are more likely to leverage digital tools to enhance SRL and learning outcomes, particularly when positive attitudes and technology-related self-efficacy are present (Asio, 2025; Vinodan & Meera, 2025).

DR, on the other hand, refers to the individual's capacity to adapt to and recover from digital challenges such as connectivity issues, social media distractions, and technological fatigue. Rooted in Resilience Theory (Luthar et al., 2000), this construct is applied in digital ecosystems where resilience supports learners in maintaining focus and motivation despite technological setbacks (Pan et al., 2024; Sun et al., 2022). The operational definition of DR in this study encompasses four core dimensions: (1) managing digital disruptions, (2) adapting to technological changes, (3) controlling distractions, and (4) recovering from digital fatigue (Garista & Pocetta, 2014; Lee & Hancock, 2023; Naeem & Mushibwe, 2025; Wright, 2016).

Conceptually, the relationships among variables in this study are explained through a synthesis of three major theoretical frameworks. Self-Determination Theory [SDT] elucidates the role of EI in fostering intrinsic motivation and self-regulation; social cognitive theory [SCT] explains the dynamic interactions among EI, DM, and SRL; while technology acceptance model and Digital Resilience Theory clarify how contextual factors moderate these relationships. Hence, the proposed model is not only empirically grounded but also theoretically anchored in well-established psychological and educational frameworks.

Empirical gaps remain evident in the literature, as prior studies often examine psychosocial dispositions, self-regulation strategies, and technological factors in isolation. Few studies have integrated EI, DM, SRL, TA, and DR within a comprehensive mediation–moderation framework, particularly in the context of senior high school students in developing countries such as Indonesia, where regional disparities in digital readiness persist (Chen et al., 2025). Therefore, this study addresses this gap through a partial least squares–structural equation modeling [PLS-SEM] approach to test theoretically grounded relationships. The study aims to contribute theoretically by extending the application of SDT, SCT, and TAM within the domain of digital economics education, and practically by informing strategies to enhance SRL through the strengthening of students' EI, DM, and DR.

A growing body of research highlights the role of EI in helping students manage academic stress, sustain motivation, and maintain productive social relationships, which in turn fosters learning engagement and academic success (Kuswanto et al., 2023; Shengyao, 2024). In addition, the construct of DM which encompasses openness to new technologies, adaptability, digital creativity, online collaboration, and data-driven problem solving has been identified as a critical predictor of how students utilize digital tools for learning purposes and develop self-directed strategies (Meng et al., 2024; Solekhah et al., 2025).

The concept of SRL serves as a central mechanism through which dispositions such as EI and DM are translated into effective learning practices, including planning, monitoring, regulating cognitive and motivational strategies, and reflecting on outcomes (Arrafii et al., 2025; Chen et al., 2025; Tinajero et al., 2024). Recent evidence suggests that technology-enriched learning environments can enhance SRL when supported by digital skills and appropriate instructional contexts (Faza & Lestari, 2025; Sui et al., 2024). Positioning SRL as a mediating variable in the research model is therefore both theoretically and practically relevant for understanding how EI and DM influence academic achievement in the context of technology-supported economics learning.

At the same time, TA and DR emerge as contextual factors that may shape the strength of psychosocial influences on learning outcomes. TA, which encompasses students' perceptions of usefulness and ease of use of technology, frequently determines their intention to use and actual engagement with learning technologies (Barrett et al., 2023; Marikyan et al., 2023; Vinodan & Meera, 2025). Meanwhile, DR reflects students' capacity to recover from digital disruptions such as connectivity problems, distractions, and digital fatigue, thus enabling continuity in learning (Pan et al., 2024; Sun et al., 2022). However, empirical evidence regarding their moderating roles remains mixed; while some studies report context-dependent effects, others suggest that TA and DR function more prominently as direct predictors or mediators rather than moderators (Setyadi et al., 2025).

This empirical gap underscores the need for research that integrates psychosocial variables (EI and DM), learning mechanisms (SRL), and contextual technology-related conditions (TA and DR) within a moderated–mediation framework. In the context of senior high schools in Padang where students are heterogeneous in terms of socioeconomic background and digital readiness testing such an integrated model is critical to producing policy- and practice-oriented recommendations. These may include designing interventions that combine the strengthening of emotional intelligence, the cultivation of digital literacy and mindset, and explicit training in SRL embedded within digital learning activities (Asio et al., 2025; Chen, 2022; Chen et al., 2025). Accordingly, this study seeks to fill this gap through empirical analysis using PLS-SEM, with the aim of generating evidence that schools can adapt to improve the effectiveness of technology-based economics learning and enhance students' resilience in the digital era (Asare & Boateng, 2025).

2. Conceptual Framework and Hypothesis Development

This study develops a conceptual framework that integrates psychosocial factors and students' digital dispositions within the context of technology-based economics learning. The model positions EI and DM as the main independent variables that are assumed to influence SRL and, in turn, students' academic achievement. SRL is proposed as a mediating variable that bridges the influence of EI and DM on learning outcomes. In addition, TA and DR are conceptualized as moderating variables that may strengthen or weaken the relationships among the core constructs in the model.

H1: Emotional intelligence has a positive effect on self-regulated learning.

Emotional intelligence facilitates students' ability to recognize, manage, and direct their emotions effectively, thereby enhancing their capacity for self-regulation in learning. Students with high levels of emotional intelligence are more capable of sustaining motivation, coping with academic stress, and adapting to new learning environments, which in turn promotes the development of self-regulated learning (Mustofa et al., 2022; Shengyao, 2024). Based on Self-Determination Theory (Deci & Ryan, 2000), emotional intelligence helps students fulfill their basic psychological needs for autonomy, competence, and relatedness prerequisites for effective self-regulation. Therefore, EI is expected to positively influence SRL by enhancing intrinsic motivation and emotional management, which support autonomous learning

H2: Emotional itelligence has a positive effect on academic achievement.

Emotional intelligence not only influences the learning process but also impacts learning outcomes through its role in regulating emotions, motivation, and social interactions. Students with high emotional intelligence tend to be more focused, disciplined, and engaged in their learning activities, resulting in better academic achievement (Barz et al., 2024; Kuswanto et al., 2023). Within the framework of Social Cognitive Theory, emotional competence reinforces academic self-efficacy, which refers to students' belief in their ability to achieve desired academic outcomes (Zimmerman, 2000). Consequently, emotionally intelligent students are more confident in overcoming digital learning challenges, which ultimately contributes to improved academic performance.

H3: Digital mindset has a positive effect on self-regulated learning.

A digital mindset encompasses openness to new technologies, adaptability, creative thinking, and the ability to integrate digital tools to achieve learning goals (Leonardi, 2022). Students with a strong digital mindset are more likely to utilize technology effectively to plan learning strategies, monitor progress, and evaluate outcomes (Solekhah et al., 2025). Drawing upon Social cognitive theory, digital mindset strengthens self-regulatory capabilities, as learners with higher digital self-efficacy perceive greater control over their learning processes. Thus, digital mindset functions as a cognitive disposition that fosters SRL through digital efficacy and mastery of technological tools.

H4: Digital Mindset has a positive effect on Academic Achievement.

Students with a strong digital mindset tend to exhibit greater engagement in technology-enhanced learning and achieve higher academic outcomes (Meng et al., 2024; Solekhah et al., 2025). From the perspective of self-determination theory, a digital mindset facilitates autonomous and meaningful learning experiences, as students use technology based on their personal interests and learning needs rather than external instructions. This autonomy fosters intrinsic motivation, which in turn enhances learning outcomes.

H5: Self-Regulated Learning has a positive effect on academic achievement.

Self-regulated learning enables students to set learning goals, plan strategies, monitor progress, and reflect on results, thereby improving academic performance. Arrafii et al. (2025) found SRL to be a significant predictor of academic achievement in digital learning environments. According to Social Cognitive Theory, SRL emerges from the interaction among personal factors (beliefs, emotions, and mindset) and the digital learning environment. Students with higher SRL can effectively transfer the control of learning from teachers to themselves, leading to improved academic outcomes.

H6: Self-Regulated Learning mediates the relationship between Emotional Intelligence and Academic Achievement.

Drawing on Self-Determination Theory and Social Cognitive Theory, Emotional Intelligence is assumed to influence learning outcomes indirectly through the enhancement of self-regulated learning. Emotional Intelligence strengthens students' capacity for self-regulation, stress management, and academic focus, which in turn contributes to better academic performance (Mustofa et al., 2022; Shengyao, 2024).

H7: Self-regulated learning mediates the relationship between digital mindset and academic achievement.

Within the framework of social cognitive theory, digital mindset enhances students' sense of efficacy and control over their learning through strategic use of technology, which is then translated into effective self-regulated learning behaviors. Higher levels of self-regulated learning enable students to apply digital tools productively to achieve optimal academic outcomes (Solekhah et al., 2025; Sui et al., 2023).

H8: Technology acceptance moderates the relationship between emotional intelligence and Academic Achievement.

Technology Acceptance, which encompasses the perceived usefulness and perceived ease of use of technology (Davis, 1989), is expected to strengthen the positive effect of emotional ıntelligence on learning outcomes. Students who perceive technology as useful and easy to use are more capable of applying their emotional competencies effectively within digital learning environments.

H9: Technology acceptance moderates the relationship between digital mindset and academic achievement.

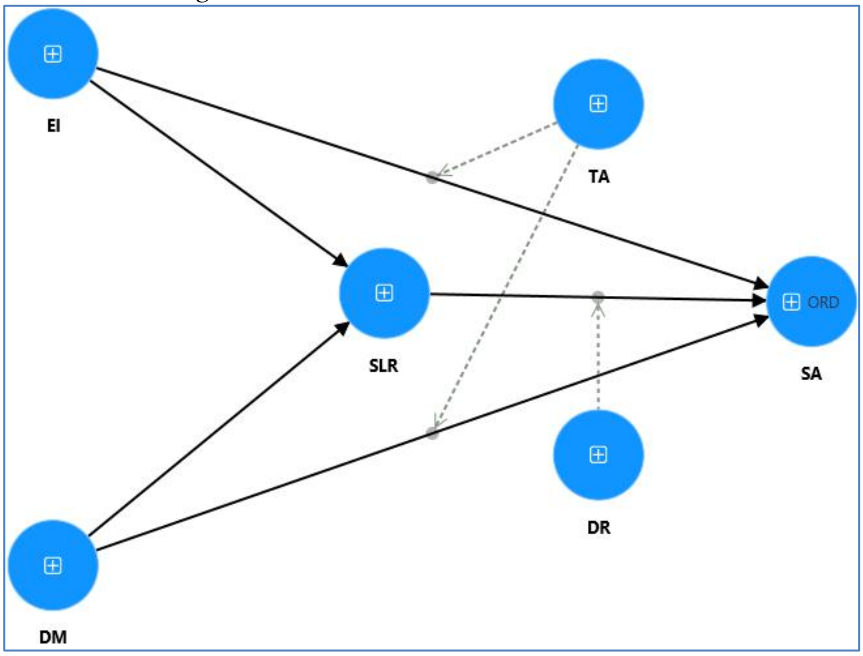
According to the technology acceptance model, the strength of the relationship between digital mindset and learning outcomes depends on the level of students' acceptance and comfort in using technology. Students with a high digital mindset but low technology acceptance may not fully utilize their digital potential, whereas those who exhibit both high digital mindset and high Technology Acceptance are likely to experience more effective learning processes.

H10: Digital Resilience moderates the relationship between self-regulated learning and academic achievement.

Digital Resilience refers to students' ability to adapt to and recover from digital disruptions such as technical issues, distractions, or digital fatigue (Lee & Hancock, 2023; Naeem & Mushibwe, 2025; Sun et al., 2022). Grounded in resilience theory, students with higher levels of Digital Resilience are expected to maintain effective self-regulation even in the face of technological challenges, thereby strengthening the relationship between self-regulated learning and learning outcomes.

Taken together, this conceptual framework integrates direct relationships, mediation, and moderation effects, offering a comprehensive perspective on the determinants of technology-based economics learning outcomes among senior high school students. The SEM model diagram illustrating the research hypotheses is presented in Figure 1.

Figure 1
SEM Model Diagram



Note. EI: Emotional intelligence; DM: Digital mindset; SLR: Self-regulated learning; TA: Technology acceptance; DR: Digital resilience; SA: Student achievement.

3. Method

3.1. Research Design

This study employed an ex post facto design with a quantitative approach, as the researcher did not manipulate the independent variables but rather analyzed the naturally occurring relationships within the learning environment. This design is appropriate for identifying both direct and indirect effects among psychosocial variables such as Emotional Intelligence, Digital Mindset, and Self-Regulated Learning on students' academic achievement. The ex post facto approach allows for the exploration of causal relationships based on empirically existing data without experimental intervention (Creswell & Creswell, 2018).

To analyze the complex interrelationships among variables, this study utilized structural equation modeling as the primary analytical tool. The use of SEM is justified because it enables simultaneous examination of multiple latent constructs, including mediation and moderation effects, within a comprehensive structural model. A detailed rationale for selecting SEM and the causal hypotheses developed in this study are elaborated in the introduction section (Byrne, 2013).

3.2. Participants

The population of this study comprised all public senior high school students in Padang City, West

Sumatra Province, totaling 18,361 students distributed across 16 schools. The sampling technique applied was proportional stratified random sampling to ensure balanced representation among schools, considering variations in student numbers across institutions.

The inclusion criteria were as follows: (1) students currently enrolled in Economics courses during the 2023/2024 academic year, and (2) those who have used digital learning media in the learning process. Based on the Slovin formula with a 5% margin of error, the minimum required sample size was 392 respondents, which is considered adequate for populations exceeding 10,000 individuals (Lakens, 2022).

The sample distribution was carried out proportionally across schools to ensure the scientific representativeness of the data, allowing for reliable generalization and replication in similar educational contexts. The demographics of the research participants are presented in Table 1.

Table 1
Distribution of participants based on demographics

Gender	*Amount*	*Percentage*
Female	255	34.9
Male	137	65.1
Total	392	100

Table 1 presents the gender-based demographic distribution of the research participants. Of the total 392 respondents, the majority were female students, numbering 255 individuals (65.1%), while male students accounted for 137 participants (34.9%). This distribution indicates a substantial predominance of female participants within the sampled population. Given that the sample was selected proportionally from the total population of each school, the observed gender composition can be considered an accurate reflection of the population structure. Consequently, the representativeness of the sample is scientifically defensible, thereby supporting the robustness of the statistical analyses and enhancing the potential for replication of the study in comparable educational settings.

3.3. Instruments

Data were collected using a structured questionnaire developed as the primary instrument within the survey method framework. The questionnaire consisted of six main sections, each designed to measure different constructs: students' economics grades, EI, DM, SRL, TA, and DR.

The dependent variable, namely students' learning outcomes in Economics, was not measured through a perception-based questionnaire but rather obtained from official school records during the ongoing semester. The data were collected through coordination with Economics subject teachers and school administrators. The grades used represented the average of formative and summative assessments from the first semester of the 2023/2024 academic year, reflecting students' cognitive achievement as outlined in the Merdeka Curriculum.

To ensure comparability across schools with potentially different grading systems, the raw scores were converted into a 0–100 scale and subsequently standardized (Z-scores). This approach was chosen to ensure that academic achievement truly reflected students' actual cognitive competence rather than subjective self-perceptions, thereby enhancing the external validity and objectivity of the learning outcome data.

In addition to students' academic achievement data, the emotional intelligence variable was measured using items adapted from Antonopoulou (2024), encompassing self-awareness, self-regulation, self-motivation, empathy, and social skills. One example of an item for this variable is: *"I am able to recognize my own feelings when I experience difficulties in understanding economics material using technology."* Digital mindset was assessed using items adapted from Neeley and Leonardi (2022), Fisher (2022), and Christy (2023), which include openness and interest in new technologies, adaptability and learning ability, creativity and innovation, digital collaboration and communication, data-driven problem solving, as well as awareness and understanding of technological trends. An example statement for this construct is: *"I enjoy trying new digital applications or platforms used in economics learning."* Digital resilience consisted of items related to awareness of online threats, knowledge of solutions, learning digital knowledge and skills, recovery from stress, and progressing through self-efficacy (Sun, 2022). A sample item is: *"I am aware of risks such as hoaxes or digital fraud when searching for economics-related information on the internet."* Self-regulated learning was measured using items related to motivation (intrinsic goal orientation, extrinsic goal orientation, task value, control of learning beliefs, self-efficacy, and test anxiety) and learning strategies (rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation, effort regulation, help-seeking, time and study environment management, and peer learning), adapted from Pintrich and Garcia (1994). One example item for this variable is: *"I am motivated to participate in technology-based economics learning because I want to genuinely understand the material."* Furthermore, technology acceptance was measured using items adapted from Graser and Böhm (2022) and Ghimire and Edwards (2024), which include perceived usefulness, perceived ease of use, attitude toward usage, and behavioral intention. An example item is: *"The use of technology helps me understand economics material better."*

The total number of items included in the questionnaire was 35 statements. All items were measured using a five-point Likert scale, with the following anchors: 5 = always, 4 = often, 3 = sometimes, 2 = rarely, and 1 = never. To ensure content validity, the questionnaire was reviewed by experts and pilot-tested prior to distribution.

3.4. Data Collection and Data Analysis

Data were collected using both online and paper-based questionnaires administered to a total of 263 valid respondents who met the inclusion criteria. The questionnaire consisted of several subscales measuring the main latent constructs of the study, namely EI, DM, SRL, TA, and DR. Each construct was measured using multiple indicators adapted from established instruments with minor contextual adjustments to suit Indonesian secondary education settings. All items were rated on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

The students' academic achievement in Economics (SA), which served as the dependent variable, was not measured through questionnaire items. Instead, it was obtained from official school records, specifically the average score of formative and summative assessments in the first semester of the 2023/2024 academic year. These raw grades were converted to a 0–100 scale and standardized (z-score) before being imported into the SEM model as a single-indicator observed variable representing academic performance.

To avoid the statistical artifact that resulted in a factor loading of 1.0, the variable was modeled as a manifest variable rather than a latent construct. This specification ensures that the academic achievement score directly reflects the observed data rather than being estimated through multiple reflective indicators. In other words, the factor loading of 1.0 is a fixed value, not an empirical estimate, as it represents a directly measured outcome variable (Byrne, 2013; Hair & Alamer, 2021).

The data collection procedure followed standard research ethics, including informed consent from participants and permission from school authorities. Data were screened for completeness, and missing responses were treated using pairwise deletion to preserve statistical validity before further analysis using PLS-SEM.

The reliability of the research instruments was assessed using Rho_A and composite reliability to ensure internal consistency. Construct validity was examined through cross-loading values, which verified that questionnaire items accurately reflected the underlying theoretical constructs. Descriptive statistics were employed to summarize respondent characteristics and to examine distributional patterns in the dataset. To test the research hypotheses, path analysis using PLS-SEM was applied, allowing for the estimation of both mediating and moderating effects within the proposed model.

3. Results

Table 2 presents the results of the reflective measurement model analysis for EI, DM, SRL, TA, DR, and SA. Based on the outer loadings, several indicators did not meet the minimum criterion (>0.50) and were therefore removed. Overall, the construct reliability for each variable demonstrated satisfactory results, with Rho_A and Composite Reliability values exceeding 0.70, indicating adequate internal consistency. In addition, the Average Variance Extracted [AVE] values for all constructs were above the threshold of 0.50, confirming that convergent validity was achieved, as each construct was able to explain more than 50% of the variance in its respective indicators.

Table 2
Results of the reflective measurement model analysis

Variables/ contruct	*Indicator/ Variable Items*	*Outer Loadings*	*Rho_A*	*Composite Reliability (CR)*	*AVE*
EI	EI1	Out	0.712	0.812	0.521
	EI2	0.608			
	EI3	0.727			
	EI4	0.738			
	EI5	0.758			
DM	DM1	0.741	0.826	0.869	0.527
	DM2	0.725			
	DM3	0.766			
	DM4	0.709			
	DM5	0.615			
	DM6	0.786			
SRL	SRL1	0.739	0.914	0.925	0.508
	SRL2	0.682			
	SRL3	0.667			
	SRL4	0.760			
	SRL5	0.589			
	SRL6	Out			
	SRL7	0.711			
	SRL8	0.791			
	SRL9	0.693			
	SRL10	0.729			
	SRL11	0.757			
	SRL12	Out			
	SRL13	0.648			
	SRL14	0.729			
	SRL15	Out			
TA	TA1	0.800	0.831	0.883	0.653
	TA2	0.842			
	TA3	0.810			
	TA4	0.779			
DR	DR1	0.723	0.822	0.867	0.566
	DR2	0.739			
	DR3	0.721			
	DR4	0.802			
	DR5	0.774			

Table 3 presents the results of the cross-loading analysis used to evaluate discriminant validity at the indicator level. The results indicate that all indicators demonstrated higher loadings on their intended constructs compared to other constructs, thereby meeting the criteria for discriminant validity. For instance, the DM indicators (DM1–DM6) showed their highest loadings on the DM construct (0.741–0.787), which were greater than their correlations with other constructs. These findings confirm that each indicator was more strongly associated with its designated construct than with others, suggesting that the measurement instrument satisfied discriminant validity and was suitable for further structural model analysis.

Table 3
Indicator (variable item) cross-loading

Indicators/ Variable Items	*DM*	*DR*	*EI*	*SA*	*SRL*	*TA*	*DR*SRL*	*TA*EI*	*TA*DM*
DM1	0.741	0.505	0.471	0.085	0.553	0.492	−0.144	−0.159	−0.079
DM2	0.725	0.545	0.475	0.136	0.509	0.485	−0.020	−0.094	−0.020
DM3	0.767	0.588	0.501	0.107	0.574	0.471	−0.071	−0.070	0.022
DM4	0.709	0.487	0.529	0.143	0.566	0.415	−0.003	−0.019	0.041
DM5	0.613	0.412	0.396	0.101	0.459	0.421	−0.123	−0.112	−0.056
DM6	0.787	0.581	0.512	0.128	0.640	0.560	−0.105	−0.097	−0.044
DR1	0.448	0.723	0.416	0.184	0.450	0.474	−0.123	−0.180	−0.089
DR2	0.566	0.739	0.555	0.138	0.525	0.444	−0.047	−0.079	−0.016
DR3	0.583	0.721	0.570	0.109	0.666	0.565	−0.249	−0.248	−0.146
DR4	0.591	0.802	0.510	0.193	0.622	0.517	−0.134	−0.136	−0.112
DR5	0.551	0.774	0.556	0.168	0.631	0.504	−0.154	−0.117	−0.100
EI2	0.367	0.486	0.608	0.057	0.342	0.288	−0.020	−0.078	0.019
EI3	0.464	0.458	0.746	0.108	0.458	0.473	−0.195	−0.314	−0.187
EI4	0.498	0.538	0.752	0.113	0.470	0.379	−0.155	−0.284	−0.137
EI5	0.562	0.498	0.769	0.185	0.533	0.480	−0.054	−0.183	−0.068
SA	0.161	0.217	0.169	1.000	0.176	0.207	−0.143	−0.204	−0.188
SRL1	0.561	0.617	0.494	0.166	0.742	0.590	−0.252	−0.210	−0.178
SRL10	0.577	0.577	0.456	0.154	0.729	0.493	−0.085	−0.070	−0.041
SRL11	0.556	0.596	0.480	0.114	0.758	0.567	−0.161	−0.129	−0.071
SRL13	0.465	0.534	0.452	0.080	0.643	0.560	−0.177	−0.222	−0.192
SRL14	0.551	0.591	0.486	0.194	0.729	0.597	−0.160	−0.208	−0.166
SRL2	0.490	0.417	0.366	0.134	0.686	0.547	−0.176	−0.133	−0.133
SRL3	0.527	0.477	0.376	0.162	0.681	0.615	−0.198	−0.166	−0.152
SRL4	0.586	0.590	0.449	0.155	0.763	0.570	−0.145	−0.092	−0.052
SRL5	0.447	0.514	0.422	0.082	0.595	0.423	0.004	−0.091	0.025
SRL7	0.556	0.520	0.481	0.055	0.711	0.489	-0.108	−0.108	−0.032
SRL8	0.617	0.556	0.458	0.096	0.797	0.517	-0.115	−0.042	−0.014
SRL9	0.564	0.484	0.498	0.103	0.698	0.486	-0.041	−0.054	−0.006
TA1	0.526	0.522	0.447	0.140	0.627	0.800	-0.140	−0.213	−0.138
TA2	0.543	0.570	0.481	0.175	0.606	0.842	−0.133	−0.238	−0.146
TA3	0.536	0.550	0.485	0.189	0.610	0.810	−0.167	−0.246	−0.162
TA4	0.512	0.485	0.428	0.158	0.599	0.779	−0.112	−0.214	−0.151
TA x EI	−0.124	−0.196	−0.306	−0.204	−0.176	−0.283	0.601	1.000	0.685
DR x SLR	−0.106	−0.180	−0.150	−0.143	−0.189	−0.172	1.000	0.601	0.683
TA x DM	−0.030	−0.122	−0.137	−0.188	−0.117	−0.186	0.683	0.685	1.000

Table 4
Adjusted R-squared coefficients

Variable	*R Square Adjusted*
SA	0.064
SRL	0.609

The Adjusted R-Square values provide a more accurate estimate of the proportion of variance explained in the endogenous variables by considering the number of predictors in the model. For

SA, the Adjusted R-Square value of 0.064 indicates that approximately 6.4% of the variance in SA can be explained by the predictor variables, while the remaining 93.6% is attributable to factors outside the model. Meanwhile, the Adjusted R-Square value of 0.609 for SRL suggests that about 60.9% of the variance in SRL is explained by the predictors, with the remaining 39.1% accounted for by external factors not included in the model. These results indicate that the model explains SRL more strongly than it does learning achievement.

Table 5 presents the path analysis results, which show both direct and indirect effects among the variables in the research model. For the direct effects, the path from EI to SRL (H1) was found to be significant, with a coefficient of 0.228 and $p < .001$. However, the direct path from EI to SA (H2) was not significant, as indicated by a coefficient of 0.024 and a p-value of .674. Furthermore, the relationship between DM and SRL (H3) was significant, with a coefficient of 0.610 and $p < .001$. Similarly, the paths from DM to SA (H4) and from SRL to SA (H5) were also significant, with coefficients of 0.263 ($p < .001$) and 0.164 ($p = .022$), respectively.

For the indirect effects, the path from EI to SA through SRL (H6) showed a coefficient of 0.038 with a p-value of .037, indicating a significant mediation effect. Similarly, the mediating effect of the path from DM to SA through SRL (H7) was also statistically significant, with a coefficient of 0.100 and a p-value of .028. These findings highlight that SRL plays a crucial role as a mediator in the relationship between EI and DM with student achievement.

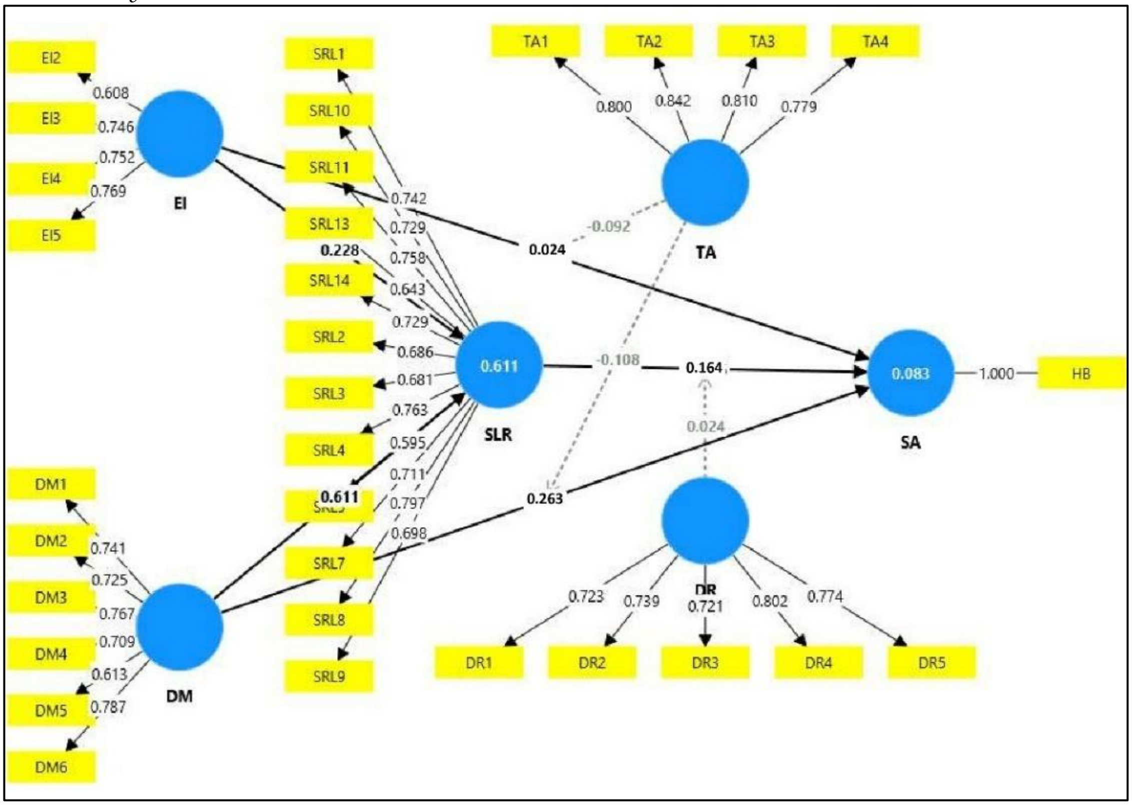
In contrast, TA did not exhibit a significant moderating role in this study. Specifically, the interaction between EI and SA through TA showed a t-statistic of 0.191 (< 1.96) and a p-value of .849 (> .05), suggesting that TA neither strengthened nor weakened the relationship between EI and SA. Likewise, the moderating effect of TA on the relationship between DM and SA was also not significant, as indicated by a t-statistic of 0.757 (< 1.96) and a p-value of .449 (> .05). Furthermore, DR as a moderator between SRL and SA also revealed non-significant results, with a t-statistic of 0.057 (< 1.96) and a p-value of 0.955 (> .05), implying that DR did not enhance or diminish the influence of SRL on SA.

Tabel 5
Path Coefficient Estimation results

Hypothesis	*Path*	*Original Sample (O)*	*T Statistics (|O/STDEV|)*	*p-values*	*Significance*
Direct Effects					
H1	EI → SRL	0.228	4.983	<.001	Significant
H2	EI → SA	0.024	0.420	.674	Not Significant
H3	DM → SRL	0.611	13.158	<.001	Significant
H4	DM → SA	0.263	4.523	<.001	Significant
H5	SRL → SA	0.164	2.286	.022	Significant
Mediation analysis					
H6	EI → SRL → SA	0.038	2.091	.037	Significant
H7	DM → SRL → SA	0.100	2.199	.028	Significant
Moderation analysis					
H8	EI*TA → SA	−0.092	0.191	.849	Not Significant
H9	DM*TA → SA	−0.108	0.757	.449	Not Significant
H10	SRL*DR → SA	0.024	0.057	.955	Not Significant

Figure 2 illustrates the relationships among the latent variables in the research model.

Figure 2
SEM Analysis Results



5. Discussion

The findings of this study confirm that emotional intelligence has a positive relationship with self-regulated learning. This indicates that students who are able to recognize, manage, and utilize their emotions effectively tend to be more capable of organizing independent learning strategies. This result aligns with Goleman's perspective on the role of emotional intelligence in self-regulation, as well as with empirical evidence showing that emotional awareness and regulation facilitate goal setting, persistence, and metacognitive control (Hemmler & Ifenthaler, 2024; Mustofa et al., 2022). Emerging empirical studies further substantiate this relationship by indicating that emotional processes are integral to learners' ability to plan, monitor, and evaluate their learning, especially within technology-supported learning environments (Panadero et al., 2023; Zheng et al., 2023). Collectively, these findings suggest that emotional intelligence serves as an essential psychological resource that strengthens learners' self-regulatory capacities in digital learning contexts.

However, emotional intelligence was not found to have a direct influence on student achievement. This suggests that emotional intelligence functions more as a foundational enabler of learning processes rather than as an immediate determinant of academic performance. This finding is consistent with Kuswanto et al. (2023), who revealed that emotional intelligence more effectively influences academic outcomes through motivation and learning strategies, and with Meng et al. (2024), who emphasized that emotional regulation facilitates learning success indirectly through engagement. Similar conclusions have been reported in prior studies indicating that emotional and motivational factors exert their strongest influence on achievement when mediated by behavioral and cognitive mechanisms such as learning engagement, self-efficacy, and self-regulated learning (Panadero & Broadbent, 2018; Zheng et al., 2023). Thus, emotional intelligence should be conceptualized as an upstream psychological construct that supports achievement through intermediate learning processes.

In contrast, digital mindset was found to have a positive effect on both self-regulated learning and student achievement. Students with a strong digital mindset tend to be more open to technology, adaptive, creative, and capable of utilizing digital resources to support autonomous learning. This finding is consistent with Solekhah et al. (2025) who identified digital mindset as a key predictor of learning success and self-regulated learning across educational systems. Empirical evidence also confirms that learners' digital readiness and positive orientation toward technology enhance their engagement in deeper learning strategies and academic performance (Zhao et al., 2024). Furthermore, supportive digital learning environments amplify the benefits of self-regulated learning when students demonstrate adaptive digital attitudes (Sui et al., 2024).

The study further demonstrates that self-regulated learning positively affects academic achievement while also serving as a key mediating mechanism in the relationships between emotional intelligence, digital mindset, and student achievement. This indicates that both emotional and cognitive dispositions translate into achievement primarily through students' ability to actively regulate their learning processes. This result strongly supports Zimmerman's (2000) social cognitive theory of self-regulated learning and is consistent with recent empirical findings emphasizing self-regulated learning as a central pathway linking psychological factors to academic success in digital learning contexts (Chen et al., 2025; Faza & Lestari, 2025). Meta-analytic and systematic review evidence also confirms that self-regulated learning is among the most robust predictors of academic achievement across learning modalities (Caixia et al., 2025; Dent & Koenka, 2016; Theobald, 2021; Zhao et al., 2025).

Meanwhile, the moderating variables technology acceptance and digital resilience did not significantly strengthen or weaken the relationships among the main variables. This suggests that students' perceptions of technology usefulness and their capacity to cope with digital challenges were relatively homogeneous, limiting their moderating potential. These findings align with Setyadi et al. (2025) and Pan et al. (2024), who reported that technology acceptance and digital resilience more often function as direct predictors rather than moderators in digitally experienced populations. Similar conclusions have been drawn in prior studies indicating that once digital learning becomes normalized, learner-centered psychological and self-regulatory factors outweigh technological perceptions in explaining learning outcomes (Maican, 2025; Yang & Lou 2024).

Taken together, these findings underscore the central role of learner-centered psychological and self-regulatory mechanisms in technology-enhanced education. Rather than relying solely on technological infrastructure or acceptance, academic success in digital learning environments appears to depend more heavily on students' emotional competencies, adaptive digital mindsets, and self-regulated learning capacities. This conclusion aligns with contemporary pedagogical frameworks emphasizing learner agency, metacognition, and emotional regulation as core elements of effective digital pedagogy (Fahrni et al., 2025; Faza & Lestari, 2025; Pacheco, 2025). By empirically demonstrating the mediating dominance of self-regulated learning and the conditional relevance of technological factors, this study contributes to international discourse advocating a shift from technology-centered interventions toward holistic, learner-centered digital education models.

6. Conclusion

This study provides empirical evidence that the success of technology-based economics learning is influenced not only by cognitive factors but also by students' psychosocial attributes and digital dispositions. The findings indicate that emotional intelligence and digital mindset play a crucial role in enhancing self-regulated learning, which in turn positively impacts academic achievement. Meanwhile, the moderating variables technology acceptance and digital resilience did not demonstrate significant roles in strengthening the relationships among the main variables. The moderated–mediation model developed in this study extends theoretical understanding of the complex relationships between emotional aspects, digital dispositions, self-regulation, and learning outcomes in the context of technology-based economics education at the high school level.

Practically, the results of this study provide implications for educators and policymakers to design interventions that not only focus on providing learning technologies but also emphasize strengthening emotional intelligence, developing a digital mindset, and training students' self-regulation skills so that they can optimally leverage technology. Future research is expected to test this model in different contexts and educational levels, as well as to expand the measurement of moderating variables to be more sensitive to variations in technology acceptance and digital resilience. Thus, the contribution of this study lies not only in advancing theories of technology-based learning but also in formulating practical strategies to improve the quality of economics learning that is adaptive to the demands of the digital era.

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Data availability: The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declaration of interest: The authors declared that there were no potential conflicts of interest.

Ethical statement: Data collection and analyses of collected data were conducted with the consent of all subjects who participated in the study. They were informed about the study's purpose, procedures, and their right to withdraw at any time without consequence.

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References

Antonopoulou, H. (2024). The value of emotional intelligence: Self-awareness, self-regulation, motivation, and empathy as key components. *Technium Education and Humanities, 11*(8), 78-92. https://doi.org/10.47577/teh.v8i.9719

Arianto, F., & Hanif, M. (2024). Evaluating metacognitive strategies and self-regulated learning to predict primary school students' self-efficacy and problem-solving skills in science learning. *Journal of Pedagogical Research, 8*(3), 301-319. https://doi.org/10.33902/JPR.202428575

Arrafii, M., Sumarsono, D., & Suadiyatno, T. (2025). Self-regulated learning strategies in distance education: Insights from Indonesia. *Journal of Pedagogical Sociology and Psychology, 7*(4), 160-173. https://doi.org/10.33902/jpsp.202534897

Asare, B., & Boateng, F. O. (2025). Self-awareness and self-regulatory learning as mediators between ChatGPT usage and pre-service mathematics teacher's self-efficacy. *Journal of Pedagogical Research, 9*(2), 38-54. https://doi.org/10.33902/JPR.202530637

Asio, J. M. R. (2025). Navigating AI-self-efficacy: Mediating student attitudes and AI literacy. *Journal of Pedagogical Sociology and Psychology, 7*(3), 49-63. https://doi.org/10.33902/jpsp.202535272

Asio, J. M. R., Cruz, A. J. D., Oconer, S. M., & Quimen Jr, V. C. (2025). Level of student attitudes towards artificial intelligence: Perspectives from nursing students. *International Journal of Didactical Studies, 6*(3), 35613. https://doi.org/10.33902/IJODS.202535613

Bandura, A. (1986). *Social foundations of thought and action: a social cognitive theory*. Prentice-Hall.

Barrett, A., Pack, A., Guo, Y., & Wang, N. (2023). Technology acceptance model and multi-user virtual reality learning environments for Chinese language education. *Interactive Learning Environments, 31*(3), 1665-1682. https://doi.org/10.1080/10494820.2020.1855209

Barz, N., Benick, M., Dörrenbächer-Ulrich, L., & Perels, F. (2024). Students' acceptance of e-learning: Extending the technology acceptance model with self-regulated learning and affinity for technology. *Discover Education, 3*(1), 114. https://doi.org/10.1007/s44217-024-00195-7

Byrne, B. M. (2013). *Structural equation modeling with Mplus: Basic concepts, applications, and programming.* Routledge.

Caixia, L., Bakar, Z. A., & Qianqian, X. (2025). Self-regulated learning and academic achievement in higher education: A decade systematic review. *International Journal of Research and Innovation in Social Science*, *9*(3), 4488-4504. https://doi.org/10.47772/IJRISS.2025.90300358

Chen, F. (2025). The relationship between digital literacy and college students' academic achievement: the chain mediating role of learning adaptation and online self-regulated learning. *Frontiers in Psychology, 16,* 1590649. https://doi.org/10.3389/fpsyg.2025.1590649

Chen, J. (2022). The effectiveness of self-regulated learning (SRL) interventions on L2 learning achievement, strategy employment and self-efficacy: A meta-analytic study. *Frontiers in Psychology, 13,* 1021101. https://doi.org/10.3389/fpsyg.2022.1021101

Chen, Z., Jalaludin, N. A., & Rasul, M. S. (2025). Exploring the mediating effect of academic self-efficacy and self-regulated learning in the relationship between teaching, social presences and cognitive presence. *Journal of Pedagogical Research, 9*(4), 157-172. https://doi.org/10.33902/JPR.202533616

Christy, M. A. (2023). Digital mindset in civil case settlement through electronic court (e-court) in the era of digital transformation. *Legal Brief, 12*(4), 382–390.

Creswell, J. W. & Creswell, J. D. (2018). *Research design: qualitative, quantitative, and mixed methods approaches.* Sage.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry, 11*(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

Dent, A. L., & Koenka, A. C. (2016). The relation between self-regulated learning and academic achievement across childhood and adolescence: A meta-analysis. *Educational Psychology Review, 28*(3), 425-474. https://doi.org/10.1007/s10648-015-9320-8

Fahrni, D. D. D., Iten, G., Prasse, D., & Hascher, T. (2025). Teachers' practices in the use of digital technology to promote students' self-regulated learning and metacognition: A systematic review. *Teaching and Teacher Education, 165,* 105150. https://doi.org/10.1016/j.tate.2025.105150

Faza, A., & Lestari, I. A. (2025). Self-regulated learning in the digital age: A systematic review of strategies, technologies, benefits, and challenges. *International Review of Research in Open and Distributed Learning, 26*(2), 23-58. https://doi.org/10.19173/irrodl.v26i2.8119

Fisher, D. S. (2022). Unfreezing and refreezing the digital mindset of businesses. *International Journal of Innovative Science and Research Technology, 7*(3), 901-905.

Garista, P. & Pocetta, G. (2014). *Digital Resilience: meanings, epistemologies, and methodologies for lifelong learning* [Paper presentation]. SIREM 2014 Conference (Società Italiana di Ricerca sull'Educazione e la Formazione), University of Padua, Padua, Italy. https://doi.org/10.13140/2.1.3552.1605

Ghimire, A. & Edwards, J. (2024). Generative AI adoption in the classroom: A contextual exploration using the technology acceptance model (TAM) and the innovation diffusion theory (IDT). In E. Board (Ed.), *Intermountain Engineering, Technology and Computing (IETC)* (pp. 129-134). IEEE. https://doi.org/10.1109/IETC61393.2024.10564292

Graser, S., & Böhm, S. (2022). *A systematic literature review on technology acceptance research on augmented reality in the field of training and education* [Paper presentation]. CENTRIC 2022 The Fifteenth International Conference on Advances in Human oriented and Personalized Mechanisms, Technologies, and Services, Lisbon.

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics, 1*(3), 100027. https://doi.org/10.1016/j.rmal.2022.100027

Hemmler, Y. M., & Ifenthaler, D. (2024). Self-regulated learning strategies in continuing education: A systematic review and meta-analysis. *Educational Research Review, 45,* 100629. https://doi.org/10.1016/j.edurev.2024.100629

Kuswanto, E., Malihah, N., Saerozi, M., & Subqi, I. (2023). Attitude in mediating the relationship between emotional maturity, emotional ıntelligence, emotional sensitivity, and teacher performance in Indonesian schools. *Journal of Pedagogical Research, 7*(5), 122-135. https://doi.org/10.33902/JPR.202322308

Lakens, D. (2022). Sample size justification. *Collabra: Psychology, 8*(1), 33267. https://doi.org/10.1525/collabra.33267

Lee, A. Y., & Hancock, J. T. (2023). Developing digital resilience: An educational intervention improves elementary students' response to digital challenges. *Computers & Education Open, 5,* Article 100144. https://doi.org/10.1016/j.caeo.2023.100144

Leonardi, P. M. (2022). *A digital mindset: What it really takes to thrive in the age of data, algorithms, and AI.* Harvard Business Review Press.

Luthar, S. S., Cicchetti, D., & Becker, B. (2000). The construct of resilience: A critical evaluation and guidelines for future work. *Child Development, 71*(3), 543–562. https://doi.org/10.1111/1467-8624.00164

Maican, C. I., Cazan, A. M., Cocoradă, E., Dovleac, L., Lixăndroiu, R. C., Maican, M. A., & Cocoradă, S. A. (2025). The role of contextual and individual factors in successful e-learning experiences during and after the pandemic–a two-year study. *Journal of Computers in Education*, *12*(2), 589-624. https://doi.org/10.1007/s40692-024-00323-0

Marikyan, D., Papagiannidis, S., & Stewart, G. (2023). Technology acceptance research: Meta-analysis. *Journal of Information Science*. Advance online publication. https://doi.org/10.1177/01655515231191177

Meng, L., Zhang, X. F., Li, J. M., & Sun, Z. Y. (2024). Occupational stigma perception and emotional labor: the role of Ambivalent occupational identification and leaders' emotional intelligence. *Current Psychology*, *43*(19), 17225-17238. https://doi.org/10.1007/s12144-024-05686-2

Mustofa, R. F., Rachmawati, M., & Nuryadin, E. (2022). Relationship between emotional intelligence and self-regulated learning of students in Biology subjects. *International Journal for Educational and Vocational Studies, 4*(1), 6819. https://doi.org/10.29103/ijevs.v4i1.6819

Naeem, N. K. & Mushibwe, C. P. (2025). Navigating digital worlds: a scoping review of skills and strategies for enhancing digital resilience among higher education students on social media platforms. *Discover Education, 4,* 39. https://doi.org/10.1007/s44217-025-00432-7

Neeley, T. & Leonardi, P. (2022). Developing a digital mindset. *Harvard Business Review, 100*(5-6), 50-55.

Pacheco, A. J., Boude Figueredo, O. R., Andrés, C., & Fontán De Bedout, L. (2025). Correction: AI-powered learning analytics for metacognitive and socioemotional development: a systematic review. *Frontiers in Education*, *10,* 1717153. https://doi.org/10.3389/feduc.2025.1717153

Pan, Q., Lan, M., Tan, C. Y., Tao, S., Liang, Q., & Law, N. (2024). Protective factors contributing to adolescents' multifaceted digital resilience for their wellbeing: A socio-ecological perspective. *Computers in Human Behavior, 155,* 108164. https://doi.org/10.1016/j.chb.2024.108164

Panadero, E. (2023). Toward a paradigm shift in feedback research: Five further steps influenced by self-regulated learning theory. *Educational Psychologist*, *58*(3), 193-204. https://doi.org/10.1080/00461520.2023.2223642

Pasipamire, N., Chigwada, J., & Maturure, R. (2025). Exploring the use and impact of artificial intelligence in higher education in Africa. *Journal of Pedagogical Sociology and Psychology, 7*(3), 108-131. https://doi.org/10.33902/jpsp.202532046

Pintrich, P. R. (2004). A conceptual framework for assessing motivation and self-regulated learning in college students. *Educational Psychology Review, 16*(4), 385–407. https://doi.org/10.1007/s10648-004-0006-x

Pintrich, P. R., & Garcia, T. (1994). Self-regulated learning in college students: Knowledge, strategies, and motivation. In P. R. Pintrich, D. R. Brown, & C. E. Winstein (Eds.), *Student motivation, cognition, and learning: Essays in honor of Wilbert J. McKeachie* (pp. 113–134). Routledge.

Setyadi, A., Pawirosumarto, S., Damaris, A. & Dharma, R. (2025). Risk management, digital technology literacy, and modern learning environments in enhancing learning innovation performance: A framework for higher education. *Education and Information Technologies, 30,* 15095–15123. https://doi.org/10.1007/s10639-025-13380-4

Shengyao, Y., Xuefen, L., Jenatabadi, H. S., Samsudin, N., Chunchun, K., & Ishak, Z. (2024). Emotional intelligence impact on academic achievement and psychological well-being among university students: the mediating role of positive psychological characteristics. *BMC Psychology, 12*(1), 389. https://doi.org/10.1186/s40359-024-01886-4

Solekhah, D. Z., Sakdiyah, F., & Silvia, F. (2025). Digital mindset and student resilience: A post-pandemic study on learning motivation in Indonesian high schools. *Education: Jurnal Sosial Humaniora dan Pendidikan*, *5*(2), 27-38.

Sui, C. J., Yen, M. H., & Chang, C. Y. (2024). Investigating effects of perceived technology-enhanced environment on self-regulated learning. *Education and Information Technologies, 29*(1), 161-183. https://doi.org/10.1007/s10639-023-12270-x

Sun, H., Yuan, C., Qian, Q., He, S., & Luo, Q. (2022). Digital resilience among individuals in school education settings: a concept analysis based on a scoping review. *Frontiers in Psychiatry*, *13*, 858515. https://doi.org/10.3389/fpsyt.2022.858515

Theobald, M. (2021). Self-regulated learning training programs enhance university students' academic performance, self-regulated learning strategies, and motivation: A meta-analysis. *Contemporary Educational Psychology*, *66*, 101976. https://doi.org/10.1016/j.cedpsych.2021.101976

Tinajero, C., Mayo, M. E., Villar, E., & Martínez-López, Z. (2024). Classic and modern models of self-regulated learning: integrative and componential analysis. *Frontiers in Psychology, 15,* 1307574. https://doi.org/10.3389/fpsyg.2024.1307574

Vinodan, A., & Meera, S. (2025). Technology adoption among Indigenous tourism stakeholders: scale development and validation. *Information Technology for Development, 31*(1), 95-123. https://doi.org/10.1080/02681102.2024.2345374

Wright, D. (2016). Toward digital resilience. *Elementa, 4,* 82. https://doi.org/10.12952/journal.elementa.000082

Yang, J., & Lou, K. (2024). Psychological determinants and technology acceptance in mobile learning for overseas students studying Chinese in China: A self-determination theory perspective. *Learning and Motivation*, *86*, 101986. https://doi.org/10.1016/j.lmot.2024.101986

Zhao, Y., Li, Y., Ma, S., Xu, Z., & Zhang, B. (2025). A meta-analysis of the correlation between self-regulated learning strategies and academic performance in online and blended learning environments. *Computers & Education*, *230*, 105279. https://doi.org/10.1016/j.compedu.2025.105279

Zhao, Y., Li, Y., Sun, Z. H., Jiang, Q., & Zhao, S. (2024). Variations in online self-regulated learning abilities among Chinese K-12 teachers across different regions and levels. *Frontiers in Psychology*, *15*, 1463287. https://doi.org/10.3389/fpsyg.2024.1463287

Zheng, J., Lajoie, S., & Li, S. (2023). Emotions in self-regulated learning: A critical literature review and meta-analysis. *Frontiers in Psychology*, *14*, 1137010. https://doi.org/10.3389/fpsyg.2023.1137010

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). Academic Press. https://doi.org/10.1016/B978-012109890-2/50031-7