Information Technology Education Journal
E-ISSN: 2809-798X; P-ISSN: 2809-7971
https://journal.unm.ac.id/index.php/INTEC/index

Utilizing AI in Digital Learning: The Role of Metacognitive Reasoning, Organizational Support, and Socioeconomic Status in Enhancing Academic Performance through Intrinsic Motivation

Andi Dio Nurul Awalia
Universitas Negeri Makassar, Makassar, Indonesia
Rosidah✉
Universitas Negeri Makassar, Makassar Indonesia
M.Miftach Fakhri
Universitas Pendidikan Indonesia, Bandung, Indonesia
Della Fadhilatunisa
Universitas Padjajaran, Bandung, Indonesia

ARTICLE INFO

Keywords:

Academic Performance; Digital Learning; Intelligence; Intrinsic Motivation; Metacognitive Reasoning; Organizational Support; Socioeconomic Status

Article History

Received: Dec 16, 2025
Revised : Jan 25, 2026
Accepted : Feb 17, 2026

ABSTRACT

Purpose – This study examines how metacognitive reasoning, organizational support, and socioeconomic status shape academic performance through the mediating role of intrinsic motivation in an artificial intelligence (AI) integrated learning environment. **Design** – A quantitative, cross-sectional design was employed. Data from 373 university students were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate relationships among the constructs. **Findings** – Metacognitive reasoning and organizational support significantly increased intrinsic motivation, which in turn positively affected academic performance. By contrast, socioeconomic status did not significantly influence intrinsic motivation or academic performance. **Research implications** – The results underscore the importance of cognitive and contextual supports in fostering student motivation and achievement. The nonsignificant effects of socioeconomic status warrant further investigation; future studies should explore additional individual and environmental factors that may shape academic outcomes in AI-enabled learning settings. **Originality** – This research advances an inclusive and effective framework for digital learning in higher education by demonstrating the central role of metacognitive skills and institutional support in designing AI-enhanced strategies that cultivate students intrinsic motivation and academic success.

To cite this article : Awalia, A. D. N., Rosidah, R., Fakhri, M. M., & Fadhilatunnisa, D. (2026). Utilizing AI in Digital Learning: The Role of Metacognitive Reasoning, Organizational Support, and Socioeconomic Status in Enhancing Academic Performance through Intrinsic Motivation. *Information Technology Education Journal*, 5(1), 1–17. https://doi.org/10.59562/intec.v5i1.261

Correspondence Author: ✉rosidah.unm.ac.id

INTRODUCTION

AI is increasingly shaping the education ecosystem through personalized learning, classroom analytics, and administrative automation, as summarized in the OECD Digital Education Outlook 2021 (OECD, 2021). Recent synthetic evidence suggests AI in education correlates with improved learning performance meta-analysis reports meaningful positive effects on learning outcomes (Mustafa et al., 2024; Zhang & Jantakoon, 2025). Smart technology enables real-time feedback and measurement of student/class engagement that helps teachers manage task transitions and reflect on their practice (OECD, 2021). At the governance level, UNESCO emphasized the need for a policy framework and human capacity so that the use of GenAI is human-centred and safe (UNESCO, 2023).

Despite this potential, AI integration still requires ethical-pedagogical testing, data protection, and user-oriented design to truly improve learning quality and system operational efficiency.

In Indonesia, the push for digital transformation through Merdeka Belajar policy takes place alongside the challenges of inequality in digital access and competence. A number of national studies note the gap between urban and rural areas in the use of learning technology (Halim & Hidayat, 2025). At the university level, student adoption of AI tools is rising; however, acceptance and sustained use are largely determined by system quality, information quality, and institutional support (Ninghardjanti et al., 2025). Teacher readiness is a key determinant; a systematic review found AI training for teachers still faces program design and ethical barriers, necessitating strengthened professional development (Aljemely, 2024). More broadly, the UNESCO global report emphasizes connectivity and the digital divide as prerequisites/constraints to the utilization of Education technology points that are relevant to the Indonesian context (UNESCO, 2023). Therefore, further research is important to assess how AI supports metacognition and personalized learning by considering infrastructure disparities as well as AI literacy improvement programs for educators.

Metacognition theory provides a foundational lens for understanding how students regulate and optimize their thinking during learning. Metacognition encompasses monitoring, controlling, and adapting learning strategies to achieve better outcomes. In AI-supported contexts, this framework is especially pertinent because AI can personalize learning to students' needs and abilities (Flavell, 1979). Accordingly, this study integrates metacognitive theory with AI applications to examine how such technologies can foster students' metacognitive development, enhance engagement, and accelerate learning outcomes. This linkage is underscored by evidence that AI can create opportunities for learners to more effectively manage and reflect on their learning processes (Zhai et al., 2024).

Prior studies indicate that AI can enhance students academic performance, particularly by delivering rapid, personalized feedback that fosters greater engagement (Yaseen et al., 2025a). AI can also create more interactive learning experiences, which may increase student motivation (Hu, 2024). However, despite growing evidence of AI's benefits, research remains limited on how AI supports metacognitive processes such as self-assessment and reflective learning. This study addresses that gap by examining how AI can strengthen students metacognitive skills and how organizational support can facilitate more effective implementation within educational institutions (Wang et al., 2025).

Most prior studies have examined AI's general impact on learning, but relatively few have explored how AI supports students' cognitive and metacognitive processes. A key limitation in the literature is the limited understanding of which factors enable successful AI implementation in education. Although many works highlight AI's transformative potential, few investigate how AI interacts with deeper determinants of student motivation and academic outcomes particularly in the Indonesian context. This study addresses that gap by analyzing the interplay among these factors and their combined effects on educational outcomes.

This study is theoretically significant because it extends metacognition theory to technology-enabled education, particularly AI-integrated settings. Metacognition offers insight into how learners monitor, regulate, and improve their own learning an increasingly salient capability as educational technologies evolve (Flavell, 1979). Practically, the study informs policy by emphasizing that effective AI implementation should account for cognitive and metacognitive factors. The findings aim to guide policymakers in creating enabling environments for AI use, especially in developing contexts such as Indonesia, where access to technology remains uneven (Chukwubueze & Vinella, 2024). More broadly, the research contributes to ongoing efforts to leverage technology to reduce educational disparities and improve learning quality across regions (Hardianingsih & Haryanto, 2025).

This study's overarching objective is to examine how AI can be effectively integrated into education to improve learning outcomes while accounting for cognitive and contextual factors. The findings are expected to inform technology-responsive education policies and support the design of a more inclusive and equitable education system across all levels of Indonesian society.

Research Question

1. How do Metacognitive Reasoning (MRS), Organizational Support (OS), and Socioeconomic Status (SS) influence Intrinsic Motivation (IM) in students?
2. Does Intrinsic Motivation (IM) mediate the relationship between Metacognitive Reasoning (MRS), Organizational Support (OS), and Socioeconomic Status (SS) on Academic Performance (AP)?

Metacognitive reasoning is an individual's capacity to recognize, regulate, and evaluate the thought processes and strategies used during learning. This capability enables students to act as active agents by selecting appropriate strategies, monitoring progress, and adjusting their approach as needed (Rivas et al., 2022). In educational settings, metacognitive reasoning is crucial for managing learning strategies effectively, particularly within metacognition-oriented instructional models and e-learning modules that foster reflection and self-evaluation (Ratnayake et al., 2024). Metacognitive activities such as strategic awareness and systematic evaluation of learning steps are positively associated with students' problem-solving skills and academic achievement (Xie, 2024). Accordingly, strengthening metacognitive reasoning is essential when designing learning interventions aimed at enhancing intrinsic motivation and sustaining improved learning outcomes.

H1: Metacognitive Reasoning (MRS) has a positive and significant effect on Intrinsic Motivation (IM).

Organizational Support in the context of education refers to students' perceptions that educational institutions, such as schools or universities, value their contributions and care about their well-being. Such support may include providing adequate resources, recognizing students' efforts, and implementing policies that promote a healthy balance between academic commitments and personal life (Tuiloma et al., 2022). The main function of organizational support is to create a supportive relationship between students and educational institutions, which in turn increases students' motivation, learning satisfaction, and academic achievement (Graham et al., 2023). In practice, educational institutions that provide tangible support, such as adequate learning facilities, academic guidance, and policies that support students' mental and physical well-being, will help students overcome their academic challenges and encourage engagement and innovation in learning. Drawing on prior empirical evidence, students' positive perceptions of organizational support significantly influence intrinsic motivation and academic performance across educational settings (Yang, 2023).

H2: Organizational Support (OS) has a positive and significant effect on Intrinsic Motivation (IM).

Socioeconomic status (SES) denotes an individual's or family's position within the social and economic hierarchy, typically measured by household income, parents' education, and employment status (Zaneva et al., 2024). This construct reflects the interplay of material and social resources that shape life circumstances, including educational experiences. In education, SES primarily influences students' access to learning resources, opportunities, and supportive environments that facilitate academic achievement. In educational practice, SES is applied as an important variable in learning equity analysis: schools and governments use SES data to design interventions to reduce learning outcome gaps between students from different backgrounds. Recent empirical evidence supports that SES is strongly correlated with student learning achievement. For example, it was found that parental socioeconomic status significantly affects students' secondary education success (Iddrisu & Alhassan, 2025; Tan, 2024).

H3: Socioeconomic Status (SS) has a positive and significant effect on Intrinsic Motivation (IM).

Intrinsic motivation is an individual's internal drive to engage in an activity due to the inherent interest, satisfaction, or challenge it provides (Zhou, 2023). The main function of intrinsic motivation is to encourage active engagement, creativity and perseverance in the learning process, rather than merely to gain external rewards. In educational practice, intrinsic motivation is applied through learning that provides autonomy, personal relevance and appropriate challenge. For example, autonomy support from teachers can slow down the decline of students' reading motivation in middle school (Hornstra et al., 2023). Recent empirical evidence suggests that students with strong intrinsic motivation tend to use deep learning strategies and achieve better results in higher education contexts (Vayre & Vonthron, 2024). As such, strengthening intrinsic motivation is central in the design of learning interventions that seek to sustainably improve student engagement, well-being in school and learning outcomes.

H4: Intrinsic Motivation (IM) has a positive and significant effect on Academic Performance (AP).

Academic Performance refers to the outcomes that students achieve in an educational context, often measured through test scores, GPA, or other curriculum achievements (Hussain, 2024). The primary purpose of measuring academic performance is to evaluate the effectiveness of the learning process and identify areas for improvement (Gupta & Singh, 2025). In practice, academic performance is used as an indicator to evaluate the quality of teaching, the effectiveness of the curriculum, and students' readiness to face academic challenges (Sánchez-Rosas et al., 2023). Empirical evidence indicates that study time, attendance, motivation, and social support are significant predictors of students' academic performance (Khairani et al., 2024). Emphasizing these factors is therefore crucial for designing interventions that can holistically improve students' academic performance, including by supporting factors that influence intrinsic motivation and academic achievement.

H5: Intrinsic Motivation (IM) mediates the influence of Metacognitive Reasoning (MRS), Organizational Support (OS), and Socioeconomic Status (SS) on Academic Performance (AP).

1. H5a: Intrinsic Motivation (IM) mediates the influence of Metacognitive Reasoning (MRS) on Academic Performance (AP).
2. H5b: Intrinsic Motivation (IM) mediates the influence of Organizational Support (OS) on Academic Performance (AP).
3. H5c: Intrinsic Motivation (IM) mediates the influence of Socioeconomic Status (SS) on Academic Performance (AP).

The theoretical framework of the research hypotheses is shown in Figure 1, which is based on the above literature review.

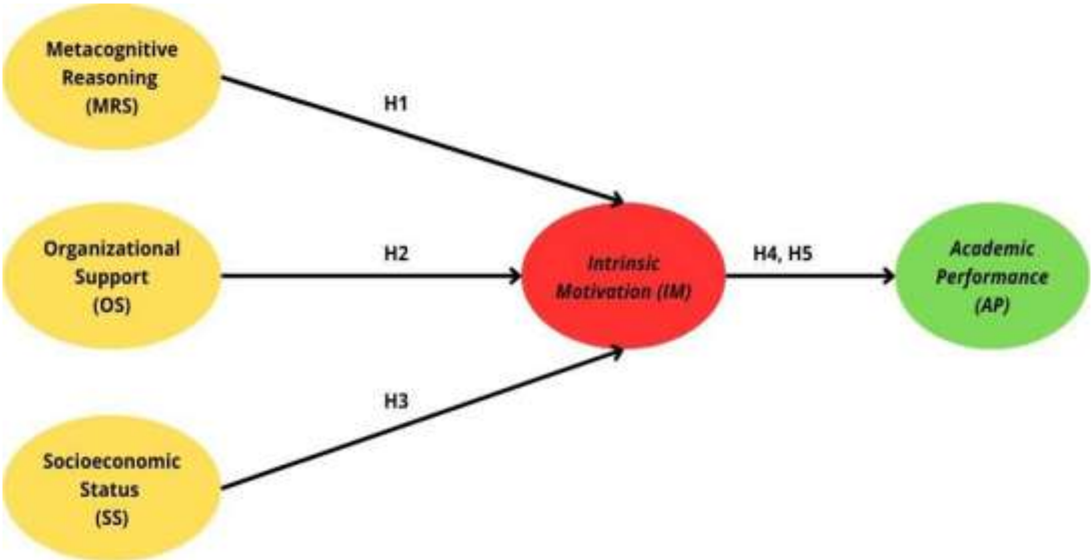

Figure 1. Theoritical Framework of the research hypothesis

METHOD

This study employs a quantitative design to examine the effects of metacognitive reasoning (MRS), organizational support (OS), and socioeconomic status (SES) on academic performance (AP), mediated by intrinsic motivation (IM). It investigates relationships among these key constructs and evaluates IM's mediating role at the intersection of cognitive and contextual factors and academic outcomes. The research was conducted in an academic environment with university students as respondents engaged in learning, and data was collected using an online survey to ensure a wide and efficient reach within the target population. Table 1 shows the survey research instruments.

Table 1. Definition

Variable	Statement
Metacognitive Reasoning (MRS)	AI Getting students to reflect on the critical factors that influence the realisation of their learning activities
	AI Make students think about whether the type of feedback received during learning activities is really helpful
	AI Getting students to think about the most appropriate information to better support their conceptual and personal change
	AI Made students reflect on alternative aspects that could have led them to make different decisions
Organizational Support (OS)	I feel supported by my educational institution in learning about and using AI technologies.
	My institution encourages innovation and the use of AI in the learning environment.
	The culture at my educational institution reduces my anxiety towards AI.
	I believe there is sufficient support to address AI technologies at my institution.
Socioeconomic Status (SS)	My socioeconomic status affects my access to AI learning resources.
	Differences in socioeconomic status among students affect their level of anxiety towards AI.
	I have the resources needed to engage with AI technologies effectively.
Academic Performance (AP)	AI Makes students think more critically about what they have learnt in this course.
	AI Allows students to reflect that certain changes (in their knowledge and skills) are evident with respect to what they initially thought or knew
	AI Getting students to remember when these changes occurred
	AI Getting students to think about what caused this change to occur
	AI Enable students to consider aspects that still confuse them
	AI Getting students to reflect on what they would like to know more about
Intrinsic Motivation (IM)	I think I am a good student
	I believe I can do well on the questions and assignments
	I think I will get good grades in this class because my learning ability is very good.
	I know that I will be able to learn the material for this class
	I prefer challenging class assignments so that I can learn new things
	I like what I am learning in this class because it is useful for me to know.
	I understand this course is important to me because I can use what I learnt in class

The research instrument was a questionnaire developed specifically for this study, consistent with standard quantitative practice. Item construction was guided by a literature review to ensure that each indicator aligned with the target constructs: Metacognitive Reasoning (MRS1–MRS4), Organizational Support (OS1–OS4), Socioeconomic Status (SES1–SES3), Intrinsic Motivation (IM1–IM7), and Academic Performance (AP1–AP6). Instrument development drew on Bai et al., (2023); Caratiquit et al., (2023); Tossell et al., (2024), and validity and reliability were assessed following. Convergent validity was evaluated using outer loadings and Average Variance Extracted (AVE); most outer loadings exceeded 0.70 and AVE values were above 0.50, indicating that the constructs were well measured (Jobin et al., 2019).

This study also evaluated discriminant validity using the Heterotrait–Monotrait (HTMT) ratio, with all values below 0.90 (Hair, 2019; Sarstedt, 2014). Instrument reliability was examined via composite reliability and Cronbach's alpha; both exceeded 0.70, indicating acceptable reliability for all constructs (Anuyahong & Pengnate, 2023; Kurbi et al., 2023; Varathan et al., 2023). Together, these results support the instrument's robustness and its capacity to yield credible data.

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS. The analysis proceeded in two stages: (1) outer-model evaluation to assess indicator validity and reliability, and (2) inner-model evaluation to test structural relationships among latent variables. The outer model assessed convergent validity, construct reliability, and discriminant validity. The inner model examined the effects of metacognitive reasoning, organizational support, and socioeconomic status on intrinsic motivation, and, in turn, the effect of intrinsic motivation on academic performance, including the mediating role of motivation. Relationship significance was evaluated using path coefficients, t-statistics, and p-values; results with $t > 1.96$ and $p < .05$ were deemed statistically significant (Hemrungrojn et al., 2022; Keller, 2021). Table 2 shows the General Description of Respondents.

Table 2. The General Description of the Respondents

Category	Subcategory	Frequency	Percentage (%)
Gender	Male	152	40.75
	Female	221	59.25
Age	17	8	2.14
	18	90	24.13
	19	180	48.26
	20	81	21.71
	21	13	3.49
	22	1	0.27
Experience	Beginner	19	5.09
	Intermediate	187	50.13
	Advanced	161	43.18
	None	6	1.61

As shown in Table 2, most respondents were female (59.25%), while males accounted for 40.75% of the sample. This distribution may reflect broader enrollment patterns in certain disciplines or greater participation by female students in digital learning initiatives. In terms of age, the most prominent group was the 19-year age group (48.26%), followed by the 18-year (24.13%) and 20-year (21.71%) age groups. This concentration of younger students is in line with the academic semester data, which shows that most respondents are in their second (48.26%) and fourth (48.26%) semesters. These figures suggest that most participants are in the early stages of their undergraduate studies, a period that is crucial for developing foundational skills in self-regulated learning and digital engagement.

A small proportion of students were in the sixth (2.95%) and eighth (0.54%) semesters, indicating a limited representation of final-year students. In terms of digital literacy, more than half of the students identified themselves as having intermediate experience with digital tools (50.13%), while most reported beginner-level experience (43.18%). Only a small percentage considered themselves to be advanced users (1.61%), and an even smaller group had no experience with digital technology at all (5.09%). This distribution suggests that most students are still building their technological fluency, which has direct implications for their readiness to engage with AI-powered educational platforms.

RESULTS AND DISCUSSION

Results from the Partial Least Squares (PLS) analysis are presented in two components the outer model and the inner model providing a comprehensive view of the relationships among the studied variables.

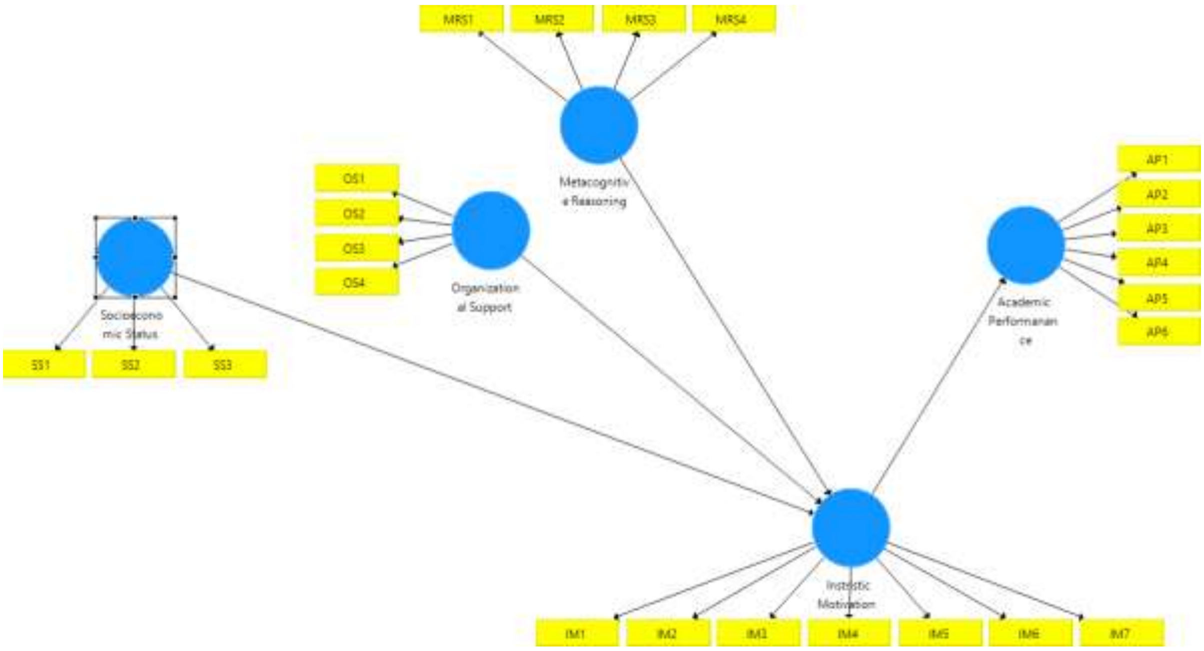

Figure 2. Outer Model/Proposed Model in this Study

Outer-model evaluation assesses the validity and reliability of the measurement instruments, with an emphasis on convergent validity under the Partial Least Squares (PLS) approach. Convergent validity was examined using outer loadings and Average Variance Extracted (AVE). As shown in Table 3, all indicators have outer loadings above 0.70, indicating strong contributions to their respective constructs. The highest loading is for OS1 (0.875), and the lowest is for IM5 (0.720); both meet recommended thresholds for convergent validity. These results suggest that the instrument demonstrates good convergent validity and that the indicators effectively represent the latent variables.

Table 3. Outer Loading

Items	Outer Loading
MRS1	0.827
MRS2	0.867
MRS3	0.840
MRS4	0.827
OS1	0.875
OS2	0.862
OS3	0.847
OS4	0.853
SS1	0.821
SS2	0.819
SS3	0.813
AP1	0.740
AP2	0.812

AP3	0.782
AP4	0.859
AP5	0.827
AP6	0.847
IM1	0.793
IM2	0.852
IM3	0.807
IM4	0.874
IM5	0.720
IM6	0.842
IM7	0.832

Table 4 presents the assessment results for the latent constructs in the PLS-SEM model: Metacognitive Reasoning (MRS), Organizational Support (OS), Socioeconomic Status (SES), Academic Performance (AP), and Intrinsic Motivation (IM). Each construct was measured with multiple indicators and evaluated using outer loadings, rho_A, composite reliability (CR), and average variance extracted (AVE).

Table 4. Rho_A, AVE and Composite Reliability

	RHO_A	Composite Reliability	AVE
Metacognitive Reasoning (MRS)	0.863	0.906	0.706
Organizational Support (OS)	0.885	0.919	0.739
Socioeconomic Status (SS)	0.779	0.858	0.669
Academic Performance (AP)	0.903	0.921	0.660
Intrinsic Motivation (IM)	0.919	0.934	0.670

The table shows that all constructs demonstrated satisfactory reliability and validity metrics. Metacognitive Reasoning (MRS) exhibits high outer loadings (0.827–0.867) with strong reliability (rho_A = 0.863, CR = 0.906, AVE = 0.706). Organizational Support (OS) achieves robust outer loadings (0.847–0.875) and reliability (rho_A = 0.885, CR = 0.919, AVE = 0.739). Socioeconomic Status (SS) shows adequate reliability and validity (outer loadings = 0.813–0.821, rho_A = 0.779, CR = 0.858, AVE = 0.669). Academic Performance (AP) and Intrinsic Motivation (IM) also exhibit strong reliability (AP: rho_A = 0.903, CR = 0.921, AVE = 0.660; IM: rho_A = 0.919, CR = 0.934, AVE = 0.670), with high outer loadings across all indicators. These results affirm the robustness of the model's constructs.

The Heterotrait–Monotrait (HTMT) ratio analysis, which assesses discriminant validity among latent constructs in the PLS-SEM model, is reported in Table 4. The examined constructs Metacognitive Reasoning (MRS), Organizational Support (OS), Socioeconomic Status (SES), Academic Performance (AP), and Intrinsic Motivation (IM) were evaluated to ensure reliability and validity within the PLS-SEM framework.

Table 5. The Heterotrait-Monotrait Ratio of Correlations (HTMT) Values

	AP	IM	MRS	OS	SS
Metacognitive Reasoning (MRS)					
Organizational Support (OS)	0.669				
Socioeconomic Status (SS)	0.886	0.726			
Academic Performance (AP)	0.807	0.649	0.841		

Intrinsic Motivation (IM)	0.802	0.531	0.763	0.738

Results of the Heterotrait-Monotrait Ratio (HTMT) the analytical results demonstrate that, as presented in table 5, show that most construct pairs have HTMT values within the acceptable range. In particular, the IM-AP (0.669), IM-OS (0.649), and IM-SS (0.531) pairs show values below the standard threshold of 0.90, which confirms that the constructs have sufficient discriminant validity and can be considered distinct.

However, certain construct pairs are close to the upper limit of 0.90. For example, the MRS-AP pair has an HTMT value of 0.886, which reflects a relatively high level of similarity but remains within acceptable limits. Similarly, the MRS-OS pair reported an HTMT value of 0.841, which indicates moderate similarity between Metacognitive Reasoning (MRS) and Organizational Support (OS) while retaining discriminant validity. The SS-OS pair showed an HTMT of 0.738, indicating a moderate relationship between Socioeconomic Status (SS) and Organizational Support (OS). Overall, these findings confirm that all constructs in the model show sufficient discriminant validity, confirming their differences despite some similarities in certain construct pairs.

Table 6. Hypothesis Test

	Hypothesis	Path Coef	T Statistic	Hypothesis	P Values
H1	MRS->IM	0.459	5.839	0.000	Positive and Significant
H2	OS->IM	0.236	3.248	0.001	Positive and Significant
H3	SS->IM	0.025	0.421	0.674	Negative and Significant
H4	IM->AP	0.612	15.978	0.000	Positive and Significant
H5a	MRS->IM->AP	0.280	5.179	0.000	Positive and Significant
H5b	OS->IM->AP	0.144	3.153	0.002	Positive and Significant
H5c	SS->IM->AP	0.015	0.417	0.677	Negative and Significant

Based on the hypothesis tests reported in Table 6, H1 indicates that metacognitive reasoning (MRS) has a significant positive effect on intrinsic motivation (IM): path coefficient = 0.459, t-statistic = 5.839, $p < .001$. This implies that students with stronger metacognitive reasoning are more likely to exhibit higher intrinsic motivation. Prior research aligns with this finding, showing that metacognitive strategies such as self-monitoring and reflection foster intrinsic motivation by promoting learner autonomy (Siregar, 2022). Additional studies further support the link between metacognitive reasoning and self-regulated learning, a construct closely associated with intrinsic motivation (Mahligawati, 2023; Zhou, 2023).

H2 indicates that organizational support (OS) has a significant positive effect on intrinsic motivation (IM), with a path coefficient of 0.236, a t-statistic of 3.248, and $p = .001$. These results suggest that students who receive stronger institutional support such as access to learning resources, mentoring, and a supportive academic climate tend to exhibit higher intrinsic motivation. Prior work concurs, showing that organizational support enhances students' autonomy and competence, both central to intrinsic motivation (Alev, 2024), and that perceived support increases engagement and motivation, which in turn improves academic performance (Kumalasari, 2024).

Hypothesis H3 reveals that Socioeconomic Status (SS) does not significantly affect Intrinsic Motivation (IM), as indicated by the path coefficient of 0.025, T-Statistic of 0.421, and P-Value of 0.674. This suggests that students' intrinsic motivation is not directly shaped by their socioeconomic background. Although previous research suggests that socioeconomic status can influence access to educational opportunities, its direct influence on intrinsic motivation remains inconclusive, possibly due to individual resilience and self-determination factors (Fazil, 2024). Research by Qu, (2023) suggests that students from lower socioeconomic backgrounds may exhibit strong intrinsic motivation due to personal aspirations and resilience, which may mitigate the impact of their socioeconomic status (Ayu & Ghazali, 2023).

Hypothesis H4 confirmed that Intrinsic Motivation (IM) significantly and positively affects Academic Performance (AP), as indicated by the path coefficient of 0.612, T-Statistic of 15.978, and P-Value of 0.000. This finding underscores the important role of intrinsic motivation in improving academic outcomes, as motivated students are more engaged in their learning, apply effective study strategies, and persist in overcoming academic challenges. Previous research supports this relationship, emphasizing that students with higher intrinsic motivation tend to perform better academically due to increased engagement and cognitive effort (Abbas et al., 2023). Moreover, intrinsic motivation has been shown to be a strong predictor of academic success across diverse educational contexts (Wahyudi, 2024).

Hypotheses H5a, H5b, and H5c test the mediating role of intrinsic motivation (IM) in links between cognitive/contextual factors and academic performance (AP). For H5a, IM mediates the effect of metacognitive reasoning (MRS) on AP (path coefficient = 0.280, t = 5.179, p < .001), indicating that MRS influences academic performance primarily through its impact on intrinsic motivation. Research confirms that metacognitive skills enhance motivation, which in turn leads to improved learning outcomes by encouraging independent problem solving and deep learning (Salas-Pilco, 2022). Furthermore, students who engage in metacognitive practices are more likely to develop intrinsic motivation, which, in turn, positively influences their academic performance (Suwarno et al., 2023).

H5b indicates that intrinsic motivation (IM) mediates the effect of organizational support (OS) on academic performance (AP), with a path coefficient of 0.144, t = 3.153, and p = .002. This suggests that institutional support enhances academic success primarily by fostering students' intrinsic motivation. Prior research aligns with this finding: when students perceive strong organizational support, they feel valued and motivated, which increases academic effort and persistence (Mohammadi, 2024). Organizational support also helps cultivate a positive learning environment that bolsters intrinsic motivation and, in turn, overall academic performance (Thomas, 2024).

H5c indicates that intrinsic motivation (IM) does not significantly mediate the effect of socioeconomic status (SES) on academic performance (AP): path coefficient = 0.015, t = 0.417, p = .677. This suggests that although SES may shape access to resources, it does not influence academic performance via IM. Prior studies point to alternative mediators such as self-efficacy and learning strategies that more strongly connect SES to academic outcomes (Lin, 2024). For example, students' self-efficacy beliefs have been shown to substantially mediate the SES achievement relationship, underscoring the importance of psychological factors in educational attainment (Nica et al., 2022).

Overall, these findings underscore the pivotal roles of metacognitive reasoning and organizational support in fostering intrinsic motivation, which, in turn, enhances academic performance. The results highlight the need for institutions to implement strategies that cultivate metacognitive skills and provide robust organizational support to optimize learning outcomes. Future research should investigate potential moderating variables that shape these relationships and assess long-term effects through longitudinal designs (Southworth et al., 2023).

Discussion

The outer-model analysis indicates that all latent constructs Metacognitive Reasoning (MRS), Organizational Support (OS), Socioeconomic Status (SES), Intrinsic Motivation (IM), and Academic Performance (AP) exhibit satisfactory convergent validity and construct reliability. All items have outer loadings above the recommended 0.70 threshold, indicating strong relationships between indicators and their respective constructs. Moreover, each construct's Average Variance Extracted (AVE) exceeds 0.50, suggesting that the corresponding latent variable explains the majority of variance in its observed indicators (Levshov et al., 2015; Rusaitis et al., 2021). These results confirm that the indicators effectively capture the intended theoretical dimensions, providing a solid foundation for evaluating the structural model.

Beyond convergent validity, construct reliability was evaluated using composite reliability (CR) and the rho_A coefficient, both of which exceeded 0.70 for all constructs. These values indicate strong internal consistency, suggesting that the measures yield stable and dependable results (Scharnowski & Kähler, 2020; Wong et al., 2020). The reliability evidence further implies that the indicators not only correlate but also coherently reflect their intended latent constructs. Collectively, these strong reliability metrics bolster the credibility of the model and confirm that the data accurately represent respondents' perceptions, motivations, and institutional experiences in AI-enhanced learning environments.

Discriminant validity was assessed using the Heterotrait–Monotrait (HTMT) ratio, a rigorous procedure commonly applied in PLS-SEM to verify construct distinctiveness. All HTMT values were below the conservative 0.90 threshold, confirming that each construct in the model is empirically distinct (Irving et al., 2018). This suggests that respondents can clearly distinguish between theoretically related concepts such as metacognitive reasoning and organizational support, or intrinsic motivation and academic performance. Establishing discriminant validity is particularly important in educational research involving closely related constructs. These findings strengthen confidence in the instrument's design and align with prior work underscoring the importance of validated measurement models in technology-enhanced learning contexts (Manacika Dharma et al., 2021; Wu & Irving, 2020). Overall, the outer-model results provide robust psychometric evidence supporting the structural integrity of the proposed research framework.

The inner-model results clarify the structural relationships among cognitive and contextual variables and their effects on intrinsic motivation. Metacognitive reasoning (MRS) exerted a strong, significant influence on intrinsic motivation (IM; $\beta = 0.459$, $t = 5.839$, $p < .001$). This suggests that students who engage in self-regulated processes planning, monitoring, and evaluating their learning are more likely to be intrinsically motivated. The finding aligns with Zhou et al., (2022), who reported that metacognitive awareness fosters autonomy and meaningful learning experiences, thereby increasing intrinsic motivation. Consistent with this, Yaseen et al., (2025) found that adaptive AI tools can strengthen metacognitive engagement, which in turn heightens motivation.

Organizational support (OS) also had a positive, significant effect on intrinsic motivation (IM; $\beta = 0.236$, $t = 3.248$, $p = .001$). This suggests that when students perceive adequate institutional support such as access to AI resources, mentorship, and a positive learning climate, they are more likely to develop internal motivation. This finding reinforces the claim Alev, (2024), which states that institutional support fosters a sense of belonging and competence, two fundamental pillars of self-determination theory. When the learning environment addresses students' needs and provides timely resources, intrinsic motivation is more likely to develop.

Interestingly, Socioeconomic Status (SS) was not found to significantly affect IM ($\beta = 0.025$, $T = 0.421$, $p = 0.674$), which suggests that intrinsic motivation may be relatively independent of students' socioeconomic background. This non-significant result could be explained by the presence of compensatory psychological factors such as personal resilience, future aspirations, or strong self-determination, as observed in the study by (Fazil, 2024). Despite inequitable access to educational resources, students from lower-SES backgrounds can sustain high levels of motivation when driven by internal goals and supported by adaptive coping strategies.

Finally, intrinsic motivation (IM) had a strong, statistically significant positive effect on academic performance (AP) ($\beta = 0.612$, $T = 15.978$, $p < 0.001$), supporting the hypothesis that motivation is a key driver of educational outcomes. These findings reinforce theoretical perspectives that emphasize intrinsic motivation as an important factor for sustained engagement and academic perseverance (Abbas et al., 2023; Wahyudi, 2024). Motivated students tend to exert more effort, apply deeper learning strategies, and achieve higher academic performance especially in AI-enhanced environments where self-regulation plays an important role.

These findings carry important implications for Indonesian higher education institutions as they modernize instructional practices through the adoption of artificial intelligence (AI). The significant effects of metacognitive reasoning and organizational support on intrinsic motivation highlight the urgent need for universities to go beyond infrastructural investments by developing pedagogical frameworks that nurture students' self-regulatory capabilities. Curriculum planning should intentionally embed activities that develop skills in planning, monitoring, and reflection that enable students to take full advantage of AI-enhanced educational technologies. In addition, professional development for teaching staff should include targeted training on integrating AI into instructional design to foster cognitive engagement and learner autonomy.

At the institutional level, prioritizing an inclusive and supportive digital learning ecosystem is essential. The strong link between organizational support and intrinsic motivation indicates that efforts should extend beyond simply providing technological tools. Effective implementation also requires ensuring access to AI-enabled platforms, offering comprehensive digital literacy initiatives, and developing adaptive academic support systems tailored to diverse learners' needs. This is especially salient in Indonesia, where substantial disparities in digital readiness persist between urban and rural campuses. Universities should therefore adopt targeted strategies to narrow this gap and guarantee equitable access to AI resources for all students. Advancing digital equity across faculties and campuses is critical to maximizing AI's educational benefits.

From a governmental perspective, these findings offer empirical justification for increased public investment in AI infrastructure for higher education. National policies should include more than just hardware procurement, but also include the development of robust systems for educator training, curriculum integration, and targeted assistance for underserved student populations. As socioeconomic status did not significantly affect intrinsic motivation in this study, it is important for the government to address structural barriers through mechanisms such as need-based scholarships, affordable digital devices and better internet connectivity. These interventions can help level the playing field, ensuring AI-powered learning environments contribute to inclusive and equitable education nationwide.

Finally, this study underscores the need for collaborative policymaking between universities and the Ministry of Education, Culture, Research, and Technology (MOECRT) National standards and quality assurance protocols are essential to guide the ethical, pedagogical, and operational integration of AI in higher education. Ongoing monitoring, stakeholder engagement, and data-driven decision-making are critical to ensure that AI implementation reduces rather than amplifies existing disparities. Future policies should also promote longitudinal research to track the long-term impacts of AI adoption and align these innovations with the broader national education and digital transformation agenda.

CONCLUSIONS

This study underscores the central roles of metacognitive reasoning and organizational support in enhancing intrinsic motivation, which, in turn, positively affects academic performance. Although socioeconomic status does not directly influence intrinsic motivation, its effects may be channeled through other psychological and contextual factors. These findings highlight the need for AI-enabled instructional strategies that cultivate metacognitive awareness and strengthen institutional support to optimize learning outcomes.

Despite its contributions, the study has limitations, including its cross-sectional design which constrains inferences about long-term effects and its reliance on self-reported data, which may introduce bias. Future research should employ longitudinal designs to track the sustained impact of AI-enhanced learning on motivation and performance. Broadening the demographic scope and incorporating additional moderating variables will further refine understanding and improve the applicability of AI-driven educational frameworks.

REFERENCES

Abbas, N., Imran, A. S., Manzoor, R., Hussain, T., & Hussain, M. (2023). Role of Artificial Intelligence Tools in Enhancing Students' Educational Performance at Higher Levels. Journal of Artificial Intelligence Machine Learning and Neural Network. https://doi.org/10.55529/jaimlnn.35.36.49

Alev, S. (2024). The Effect of School Administrators' Use of Motivational Language on Teachers' Organizational Support Perceptions and Work Engagement. Cukurova University Faculty of Education Journal. https://doi.org/10.14812/cuefd.1355418

Aljemely, Y. (2024). Challenges and best practices in training teachers to utilize artificial intelligence: A systematic review. Frontiers in Education, 9, 1470853. https://doi.org/10.3389/feduc.2024.1470853

Anuyahong, B., & Pengnate, W. (2023). Developing a New Approach to Teaching English Vocabulary Using Mnemonics and Memory Techniques. International Journal of Research Publication and Reviews, 4(4), 3100–3106. https://doi.org/10.55248/gengpi.4.423.35573

Ayu, M. A., & Ghazali, A. (2023). The Impact of Perceived Organizational Support on Employee Motivation in Indonesia Technology Startup Companies Post Pandemic Covid 19. International Journal of Current Science Research and Review. https://doi.org/10.47191/ijcsrr/v6-i5-48

Bai, L., Liu, X., & Su, J. (2023). ChatGPT: The cognitive effects on learning and memory. Brain-X, 1(3), e30. https://doi.org/10.1002/brx2.30

Caratiquit, K. D., Caratiquit, L. J. C., & Lal-lo National High School, Cagayan, Philippines. (2023). ChatGPT as an academic support tool on the academic performance among students: The mediating role of learning motivation. Journal of Social, Humanity, and Education, 4(1), 21–33. https://doi.org/10.35912/jshe.v4i1.1558

Chukwubueze, N. V., & Vinella, O. (2024). Artificial intelligence and future of secondary education in Delta State: Implications for educational administration. Journal of Asian Scientific Research, 14(3), 277–288. https://doi.org/10.55493/5003.v14i3.5073

Fazil, A. W. (2024). Exploring the Broad Impact of AI Technologies on Student Engagement and Academic Performance in University Settings in Afghanistan. Riggs Journal of Artificial Intelligence and Digital Business. https://doi.org/10.31004/riggs.v2i2.268

Flavell, J. H. (1979). Metacognition and cognitive monitoring: A new area of cognitive–developmental inquiry. American Psychologist, 34(10), 906–911. https://doi.org/10.1037/0003-066X.34.10.906

Graham, C., Borup, J., Tuiloma, S., Martínez Arias, A., Parra Caicedo, D. M., & Larsen, R. (2023). Institutional support for academic engagement in online and blended learning environments: Exploring affective, behavioral, and cognitive dimensions. Online Learning, 27(3), 4–40. https://doi.org/10.24059/olj.v27i3.4001

Gupta, R., & Singh, P. (2025). Assessing academic performance using multidimensional indicators: A data-driven framework for higher education institutions. Education and Information Technologies, 30(2), 217–234. https://doi.org/10.1007/s10639-025-12478-2

Hair, C. M., J. F. ,. Risher, J. J. ,. Sarstedt, M. ,. &. Ringle. (2019). Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business

Review, 31(1), 2–24. Https://doi.org/10.1108/EBR-11-2018-0203. https://doi.org/10.1108/EBR-11-2018-0203

Halim, U., & Hidayat, N. (2025). The sequential levels of the digital divide in the educational domain among Indonesian university students. INJECT, 10(1), 179–208. https://doi.org/10.18326/inject.v10i1.4427

Hardianingsih, R., & Haryanto, H. (2025). The effect of learning motivation and roboguru integration on metacognition in independent learning. International Journal of Community Education and Practice. https://www.journal.payungi.org/index.php/ijcep/article/download/86/61

Hemrungrojn, S., Amrapala, A., & Maes, M. (2022). Construction of a Short Version of the Montreal Cognitive Assessment (MoCA) Rating Scale Using Partial Least Squares Analysis. https://doi.org/10.1101/2022.05.05.22274726

Hornstra, L., Stroet, K., & Van der Veen, I. (2023). Autonomy-supportive teaching and the development of students' intrinsic reading motivation in secondary education: A longitudinal study. Contemporary Educational Psychology, 74, 102147. https://doi.org/10.1016/j.cedpsych.2023.102147

Hu, S. (2024). The Effect of Artificial Intelligence-Assisted Personalized Learning on Student Learning Outcomes: A Meta-Analysis Based on 31 Empirical Research Papers. Science Insights Education Frontiers, 24(1), 3873–3894. https://doi.org/10.15354/sief.24.re395

Hussain, A. (2024). The Impact of Artificial Intelligence on Digital Media Content Creation. International Journal of Innovative Science and Research Technology (IJISRT), 998–1003. https://doi.org/10.38124/ijisrt/IJISRT24JUL927

Iddrisu, H. M., & Alhassan, A. S. (2025). The impact of parents' socioeconomic status on students' educational success in senior high schools in the Northern Region of Ghana. International Journal of Educational Researchers, 16(2), 49–64. https://doi.org/10.29329/ijer.2025.1320.3

Irving, J. C. E., Cottaar, S., & Lekić, V. (2018). Seismically Determined Elastic Parameters for Earth's Outer Core. Science Advances. https://doi.org/10.1126/sciadv.aar2538

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. Nature Machine Intelligence, 1(9), 389–399. https://doi.org/10.1038/s42256-019-0088-2

Keller, J. M. (2021). Motivational Design for Learning and Performance: The ARCS Model Approach (2nd ed.). Springer. https://doi.org/10.1007/978-3-030-62234-8

Khairani, A. Z., Ismail, N. H., & Salleh, N. M. (2024). Social support, attendance, and motivation as determinants of academic achievement among secondary students in Malaysia. Journal of Educational Research, 117(3), 341–355. https://doi.org/10.1080/00220671.2024.2320457

Kumalasari, L. D. (2024). The Mediating Role of Intrinsic Motivation in the Relationship Between Organizational Support and Quantitative Workload and Work-Related Fatigue. Jurnal Sains Psikologi. https://doi.org/10.17977/um023v13i12024p28-41

Kurbi, H. A., Abebe, S. M., Mengistu, N. W., Ayele, T. A., & Toni, A. T. (2023). Cultural Adaptation and Validation of the Amharic Version of the World Health Organization's Self Reporting Questionnaire (SRQ-20) Screening Tool Among Pregnant Women in North West Ethiopia, 2022: A Psychometric Validation. International Journal of Women's Health, 15, 779–791. https://doi.org/10.2147/IJWH.S402865

Levshov, D., Michel, T., Arenal, R., Tran, H.-N., Than, T. X., Paillet, M., Yuzyuk, Yu. I., & Sauvajol, J. L. (2015). Interlayer Dependence of G-Modes in Semiconducting Double-Walled Carbon Nanotubes. The Journal of Physical Chemistry C. https://doi.org/10.1021/acs.jpcc.5b05888

Lin, X. (2024). Exploring the Role of ChatGPT as a Facilitator for Motivating Self-Directed Learning Among Adult Learners. Adult Learning, 35(3), 156–166. https://doi.org/10.1177/10451595231184928

Mahligawati, F. (2023). Artificial Intelligence in Physics Education: A Comprehensive Literature Review. Journal of Physics: Conference Series. https://doi.org/10.1088/1742-6596/2596/1/012080

Manacika Dharma, I. W., Sari, D. P., & Rahmat, B. (2021). Validity and Reliability Test of the Short Form-36 (SF-36) Item Health Survey in Indonesian Version of Post-Heart Attack Patients in Mataram City. Advances in Health Sciences Research. https://doi.org/10.2991/ahsr.k.220206.066

Mohammadi, Y. (2024). Students as Collaborative Partners. ASCILITE Publications. https://doi.org/10.14742/apubs.2024.1196

Mustafa, M. Y., Wang, J., & Bond, M. (2024). A systematic review of literature reviews on artificial intelligence in education. Smart Learning Environments, 11, 35. https://doi.org/10.1186/s40561-024-00350-5

Nica, E., Potcovaru, A.-M., & Pădurariu, I. (2022). The Effect of Intrinsic and Extrinsic Motivation on Civil Servants' Performance. https://doi.org/10.24818/imc/2021/04.10

Ninghardjanti, P., Subarno, A., Winarno, & Umam, M. C. (2026). Evaluating AI adoption among university students in Indonesia. Research and Practice in Technology Enhanced Learning, 21, 014. https://doi.org/10.58459/rptel.2026.21014

OECD. (2021). OECD Digital Education Outlook 2021: Pushing the frontiers with AI, blockchain and robots. OECD Publishing. https://doi.org/10.1787/589b283f-en

Qu, Y. (2023). The Academic Outcomes of Logical Reasoning and Metacognitive Strategy Training for Seventh Graders: Evidence From a Quasi-Experimental Design. In Lecture Notes in Education Psychology and Public Media. https://doi.org/10.54254/2753-7048/2/2022314

Ratnayake, A., Bansal, A., Wong, N., Saseetharan, T., Prompiengchai, S., Jenne, A., Thiagavel, J., & Ashok, A. (2024). All "wrapped" up in reflection: Supporting metacognitive awareness to promote students' self-regulated learning. Journal of Microbiology & Biology Education, 25(1), e0010323. https://doi.org/10.1128/jmbe.00103-23

Rivas, S. F., Saiz, C., & others. (2022). Metacognitive strategies and development of critical thinking in higher education. Frontiers in Psychology, 13, 913219. https://doi.org/10.3389/fpsyg.2022.913219

Rusaitis, L., Khurana, K. K., Kivelson, M. G., & Walker, R. J. (2021). Quasiperiodic 1-Hour Alfvén Wave Resonances in Saturn's Magnetosphere: Theory for a Realistic Plasma/Field Model. Geophysical Research Letters. https://doi.org/10.1029/2020gl090967

Salas-Pilco, Z., S. Z. ,. Yang, Y. ,. &. Zhang. (2022). Salas-Pilco, S. Z., Yang, Y., & Zhang, Z. (2022). Student engagement in online learning in Latin American higher education during the COVID-19 pandemic: A systematic review. British Journal of Educational Technology, 53(3), 593–619. Https://doi.org/10.1111/bjet.13190. https://doi.org/10.1111/bjet.13190

Sánchez-Rosas, J., Moreno, J. E., & Ocampo, D. (2023). Academic performance as a function of student engagement and instructional quality: A cross-sectional analysis. Educational Psychology Review, 35(4), 1227–1251. https://doi.org/10.1007/s10648-023-09751-1

Sarstedt, J. F., M. ,. Ringle, C. M. ,. Henseler, J. ,. &. Hair. (2014). Sarstedt, M., Ringle, C. M., Henseler, J., & Hair, J. F. (2014). On the Emancipation of PLS-SEM: A Commentary on Rigdon (2012). Long Range Planning, 47(3), 154–160. Https://doi.org/10.1016/j.lrp.2014.02.007. https://doi.org/10.1016/j.lrp.2014.02.007

Scharnowski, S., & Kähler, C. J. (2020). Investigation of the Base Flow of a Generic Space Launcher With Dual-Bell Nozzle. CEAS Space Journal. https://doi.org/10.1007/s12567-020-00333-5

Siregar, Z. M. E. (2022). Extrinsic Motivation and Organizational Commitment: A Literature Review. International Journal of Business, Technology and Organizational Behavior (IJBTOB). https://doi.org/10.52218/ijbtob.v2i4.214

Southworth, J., Migliaccio, K. W., Glover, J., Glover, J., Reed, D., McCarty, C., Brendemuhl, J. H., & Thomas, A. M. (2023). Developing a Model for AI Across the Curriculum: Transforming the Higher Education Landscape via Innovation in AI Literacy. Computers and Education: Artificial Intelligence. https://doi.org/10.1016/j.caeai.2023.100127

Suwarno, S., Kesuma, I. M., Aprianto, R., Anggraini, S. D., Nuraini, B., Paleni, H., & Surajiyo, S. (2023). Perceived Organization Support and Work Engagement Toward Employee Performance With Motivation as Mediating Variable. Journal of Business Management and Economic Development. https://doi.org/10.59653/jbmed.v1i02.136

Tan, C. Y. (2024). Socioeconomic status and student learning: Insights from an umbrella review. Educational Psychology Review, 36, Article 100. https://doi.org/10.1007/s10648-024-09929-3

Thomas, T. (2024). The Role of Artificial Intelligence in Formal and Informal Education for Students. International Journal for Research in Applied Science and Engineering Technology. https://doi.org/10.22214/ijraset.2024.58738

Tossell, C. C., Tenhundfeld, N. L., Momen, A., Cooley, K., & De Visser, E. J. (2024). Student Perceptions of ChatGPT Use in a College Essay Assignment: Implications for Learning, Grading, and Trust in Artificial Intelligence. IEEE Transactions on Learning Technologies, 17, 1069–1081. https://doi.org/10.1109/TLT.2024.3355015

Tuiloma, S., Graham, C. R., Borup, J., Martínez Arias, A. M., Parra Caicedo, D. M., & Larsen, R. (2022). Providing institutional support for academic engagement in online and blended learning programs. Education Sciences, 12(10), 641. https://doi.org/10.3390/educsci12100641

UNESCO. (2023). Global Education Monitoring Report 2023: Technology in education—A tool on whose terms? UNESCO Publishing. https://doi.org/10.54676/UZQV8501

Varathan, K., Kumar, V. K. C., Subramanian, S. S., Alfawaz, S. S., Alzahrani, G. A., Sriraghunath, S., Priya, H., Senthil, P., Eswaramoorthi, V., & Gaowgzeh, R. A. (2023). Validation of the exercise protocol satisfaction questionnaire by content validation method. Fizjoterapia Polska, 23(4), 22–27. https://doi.org/10.56984/8ZG20AD8A

Vayre, E., & Vonthron, A.-M. (2024). Academic motivation profiles and their impact on students' engagement, well-being, and achievement in higher education. Learning and Individual Differences, 112, 102383. https://doi.org/10.1016/j.lindif.2024.102383

Wahyudi, Z. (2024). The Influence of Perceived Organizational Support and Organizational Citizenship Behavior (OCB) on Job Satisfaction With Motivation as an Intervening Variable at the IT Rabbani Sutera Foundation. Journal of Infosci. Education and Management Business. https://doi.org/10.62357/joseamb.v3i1.258

Wang, P., Liu, T., Yang, Y., & Xiang, X. (2025). Optimizing self-regulated learning: A mixed-methods study on GAI 's impact on undergraduate task strategies and metacognition. British Journal of Educational Technology, bjet.70018. https://doi.org/10.1111/bjet.70018

Wong, M., Chung, P., & Leung, K. (2020). Speed of processing and personality: The influence of personality and extrinsic feedback on the performance of cognitive tasks. Behavioral Sciences, 10(4), 76. https://doi.org/10.3390/bs10040076

Wu, W., & Irving, J. C. E. (2020). Array-Based Iterative Measurements of Travel Times and Their Constraints on Outermost Core Structure. Journal of Geophysical Research: Solid Earth. https://doi.org/10.1029/2019JB018162

Xie, R. (2024). A Study of People's Impulse Spending Psychology under the Influence of Online Social Media. Lecture Notes in Education Psychology and Public Media, 56(1), 53–60. https://doi.org/10.54254/2753-7048/56/20241636

Yang, Y. (2023). Impact of organizational support on students' information and communication technology self-efficacy, engagement, and satisfaction in a blended learning environment: An empirical study. SAGE Open, 13(4), 1–15. https://doi.org/10.1177/21582440231216527

Yaseen, H., Mohammad, A. S., Ashal, N., Abusaimeh, H., Ali, A., & Sharabati, A.-A. A. (2025a). The Impact of Adaptive Learning Technologies, Personalized Feedback, and Interactive AI Tools on Student Engagement: The Moderating Role of Digital Literacy. Sustainability, 17(3), 1133. https://doi.org/10.3390/su17031133

Yaseen, H., Mohammad, A. S., Ashal, N., Abusaimeh, H., Ali, A., & Sharabati, A.-A. A. (2025b). The Impact of Adaptive Learning Technologies, Personalized Feedback, and Interactive AI Tools on Student Engagement: The Moderating Role of Digital Literacy. Sustainability, 17(3), 1133. https://doi.org/10.3390/su17031133

Zaneva, M., Dumbalska, T., Reeves, A., & Bowes, L. (2024). What do we mean when we talk about socioeconomic status? Implications for measurement, mechanisms and interventions from a critical review on adolescent mental health. General Psychiatry, 37(6), e101455. https://doi.org/10.1136/gpsych-2023-101455

Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. Smart Learning Environments, 11(1), 28. https://doi.org/10.1186/s40561-024-00316-7

Zhang, J., & Jantakoon, T. (2025). Meta-analysis of artificial intelligence in education. Higher Education Studies, 15(2), 189–207. https://doi.org/10.5539/hes.v15n2p189

Zhou, J., L. ,. &. Li. (2023). Zhou, L., & Li, J. (2023). The Impact of ChatGPT on Learning Motivation: A Study Based on Self-Determination Theory. Education Science and Management, 1(1), 19–29. Https://doi.org/10.56578/esm010103. https://doi.org/10.56578/esm010103

Zhou, J., Zhang, J., Hua, W., & Zhao, M. (2022). How Does Enlistment Motivation Shape Organizational Commitment? The Role of Career Identity and Organizational Support. Psychological Reports. https://doi.org/10.1177/00332941221109097