

AI Acceptance and Learning Discipline in Vocational Mathematics Education

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Abstract

This study examines the relationships among students' acceptance of artificial intelligence (AI) for mathematics learning, self-regulated learning (SRL), and learning discipline. The proposed model extends a partial Technology Acceptance Model (TAM) by incorporating perceived ease of use (PEOU), perceived usefulness (PU), attitude toward use (ATU), and behavioural intention (BI), together with SRL and learning discipline. A quantitative cross-sectional survey was conducted with 206 vocational high school students (*Sekolah Menengah Kejuruan/SMK*) from DKI Jakarta, West Java, Central Java, and East Java, Indonesia. Data were analysed using partial least squares structural equation modelling (PLS-SEM). The results supported the TAM sequence: PEOU was positively associated with PU ($\beta = .743, p < .001$), PU with ATU ($\beta = .738, p < .001$), and ATU with BI ($\beta = .851, p < .001$). PU was positively associated with SRL ($\beta = .393, p < .001$), whereas BI was not significantly associated with SRL ($\beta = .131, p = .195$). SRL was positively associated with learning discipline ($\beta = .593, p < .001; f^2 = .494$). The model explained 24.1% of the variance in SRL and 45.2% of the variance in learning discipline. Mediation analysis showed a significant indirect association between PU and learning discipline through SRL ($\beta = .233, 95\% \text{ CI } [.115, .348], p < .001$), while the direct association between PU and learning discipline remained significant ($\beta = .140, p = .030$), indicating partial mediation. These findings suggest that perceived usefulness may be more educationally relevant than behavioural intention for understanding SRL and learning discipline in AI-supported mathematics learning.

Keywords:

artificial intelligence in mathematics education; technology acceptance model; self-regulated learning; learning discipline

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INTRODUCTION

Artificial intelligence (AI) is increasingly reshaping teaching and learning by providing personalised explanations, adaptive support, automated feedback, and on-demand assistance. Reviews of AI in education indicate that AI applications are expanding across educational contexts, although their educational value depends on how they are integrated into learning processes rather than simply on their technological availability (Crompton & Burke, 2023; Ouyang et al., 2022). In mathematics education, this development is particularly relevant because students frequently need explanations of abstract concepts, alternative solution strategies, timely feedback, error identification, and opportunities to revise their reasoning. Recent studies specifically addressing AI and mathematics education have highlighted the potential of AI to support personalised learning and problem solving while also emphasising the need for pedagogically purposeful implementation (Gabriel et al., 2025; Kuo et al., 2026).

The expansion of generative AI has nevertheless created an important pedagogical tension. AI can provide rapid assistance and reduce barriers to accessing explanations, but unrestricted use may also encourage students to obtain solutions without sufficiently engaging with the underlying reasoning process. Evidence from high school mathematics indicates that unrestricted generative AI can improve performance during AI-assisted practice while undermining unaided learning when students rely on the technology as a substitute for independent problem solving; instructional safeguards can mitigate these risks (Bastani et al., 2025). These findings indicate that the educational significance of AI cannot be evaluated solely in terms of access, acceptance, or immediate task performance. Attention must also be directed toward the learning processes through which students use and regulate AI.

In this study, AI-supported mathematics learning refers to students' use of AI-based digital tools to support mathematics learning activities, including obtaining explanations of mathematical concepts, checking solution procedures, generating alternative solution strategies, identifying errors, and revising mathematical work. The study does not evaluate a single proprietary AI platform. Instead, it examines students' perceptions and acceptance of AI tools used as learning support in mathematics. This operational definition is important because the study investigates the educational role of perceived AI usefulness and acceptance rather than the effectiveness of a particular AI application.

The Technology Acceptance Model (TAM) provides an established framework for explaining technology acceptance. Davis (1989) proposed that perceived ease of use and perceived usefulness are central determinants of technology acceptance, while subsequent extensions incorporated attitudes and behavioural intentions into explanations of technology use. Venkatesh and Davis (2000) further demonstrated the relevance of perceived usefulness and related acceptance constructs across longitudinal field studies. TAM has consequently been widely applied to educational technologies and provides a useful starting point for understanding students' acceptance of AI.

However, the conventional focus of TAM is primarily technological acceptance and behavioural intention. Knowing that students perceive AI as useful and intend to use it does not necessarily explain whether they employ AI in ways that support meaningful learning. This limitation becomes especially important in mathematics, where students must not only obtain answers but also plan approaches, monitor procedures, evaluate intermediate results, identify errors, and revise strategies. A student may intend to use AI because it is convenient or interesting while still using the technology primarily to obtain answers.

Self-regulated learning (SRL) provides an important theoretical bridge between technology acceptance and learning behaviour. SRL concerns learners' ability to plan, monitor, regulate, and evaluate their learning activities in pursuit of academic goals (Zimmerman, 1989, 2002). In mathematics, these processes are particularly important because successful problem solving involves selecting appropriate strategies, monitoring the validity of procedures, responding to difficulties, and evaluating the reasonableness of solutions. Research in mathematics learning has demonstrated the importance of SRL for understanding students' engagement and learning processes (Dai et al., 2022). Recent scholarship on AI and learning regulation further suggests that AI may support regulation when it is embedded in activities involving planning, feedback, monitoring, and reflection (Järvelä et al., 2023; Jin et al., 2023; Lan & Zhou, 2025).

The relationship between SRL and learning discipline is also theoretically important. In the present study, learning discipline refers to students' consistent and responsible engagement in learning activities, including regular study habits, timely

completion of learning tasks, persistence in the face of difficulties, adherence to learning goals, and responsibility for maintaining planned learning routines. Although SRL and learning discipline are related, they represent different aspects of learning. SRL describes the processes through which learners regulate cognition, motivation, behaviour, and learning strategies, whereas learning discipline describes the consistency and responsibility with which learning behaviour is maintained. SRL is therefore positioned as an antecedent of learning discipline because learners who can plan, monitor, regulate, and evaluate their learning may be better able to maintain consistent learning routines.

This distinction is particularly relevant in vocational high schools (*Sekolah Menengah Kejuruan/SMK*). Vocational students are expected to develop not only academic knowledge but also responsible, consistent, and task-oriented learning habits that support technical training and future workplace preparation. Mathematics learning within vocational education requires students to sustain effort, follow procedures accurately, check their work, and complete assigned tasks responsibly. Consequently, understanding the relationships among AI acceptance, SRL, and learning discipline is relevant to both mathematics education and vocational preparation.

Despite the growing literature on AI in education and technology acceptance, an important research gap remains. Previous studies have extensively examined whether learners perceive AI and other digital technologies as useful, easy to use, acceptable, or worthy of continued adoption. However, comparatively little attention has been paid to whether these acceptance perceptions are associated with learning-process constructs such as SRL, and whether SRL is subsequently related to disciplined learning behaviour. This gap is particularly relevant in vocational mathematics education, where students' capacity to regulate their learning and sustain responsible learning routines is important.

The present study addresses this gap by extending a partial TAM framework beyond behavioural intention. The model includes PEOU, PU, ATU, and BI together with SRL and learning discipline. The TAM component is deliberately partial and does not claim to reproduce the complete classical TAM. Instead, it selects relationships that are theoretically relevant to AI-supported mathematics learning. All constructs are modelled reflectively, meaning that the observed indicators are treated as manifestations of their respective underlying latent constructs.

The novelty of this study lies in connecting technology acceptance to two educational constructs that extend beyond conventional TAM research: SRL, a learning-process construct, and learning discipline, a behavioural learning outcome. Rather than treating behavioural intention as the endpoint of technology acceptance, the study examines whether perceived usefulness and behavioural intention are associated with students' self-regulation and whether SRL is associated with disciplined learning behaviour.

The study has both theoretical and practical significance. Theoretically, it extends the application of TAM into an educational-process framework by positioning SRL and learning discipline beyond the conventional acceptance sequence. It also examines whether PU has greater educational relevance than BI in explaining SRL. Practically, the findings may help mathematics teachers design AI-supported activities that emphasise purposeful use rather than unrestricted access. Such activities can require students to explain their reasoning, check procedures, identify errors, compare alternative strategies, and reflect on their learning.

Hypotheses and Research Questions

H1: Perceived ease of use positively influences perceived usefulness.

- H2: Perceived usefulness positively influences attitude toward use.
 H3: Attitude toward use positively influences behavioural intention.
 H4: Perceived usefulness positively influences self-regulated learning.
 H5: Behavioural intention positively influences self-regulated learning.
 H6: Self-regulated learning positively influences learning discipline.
 H7: Self-regulated learning mediates the relationship between perceived usefulness and learning discipline.
 RQ1: To what extent are students' perceptions of AI acceptance, particularly perceived usefulness and behavioural intention, associated with self-regulated learning in mathematics?
 RQ2: To what extent is self-regulated learning associated with learning discipline, and does it mediate the relationship between perceived AI usefulness and learning discipline?

METHODS

Research Design and Participants

This study employed a cross-sectional online survey design. Data were collected from January to March 2026 using a structured questionnaire administered through Google Forms. Participants were recruited using convenience sampling through available school and educational networks. The study involved vocational high school students (*Sekolah Menengah Kejuruan/SMK*) from four Indonesian provinces: DKI Jakarta, West Java, Central Java, and East Java. The names and identities of the participating schools were not reported to maintain institutional confidentiality.

The participants comprised students enrolled in Grades X, XI, and XII. A total of 206 valid responses were obtained and included in the analysis. The participants consisted of 80 Grade X students (38.8%), 60 Grade XI students (29.1%), and 66 Grade XII students (32.0%). By gender, 48 participants were male (23.3%), and 158 were female (76.7%).

The study did not impose specific inclusion or exclusion criteria beyond participation as a vocational high school student and completion of the questionnaire; the sample reflects students who were accessible through the participating educational networks and voluntarily responded to the online survey. This sampling approach was adopted to facilitate access to vocational high school students across multiple provinces while maintaining the confidentiality of participating schools.

The adequacy of the sample size was considered in relation to the proposed PLS-SEM model. The endogenous construct with the largest number of predictors was self-regulated learning (SRL), which was specified as being associated with two predictors: perceived usefulness (PU) and behavioural intention (BI). Accordingly, the structural model included at most two predictors for an endogenous construct. An a priori statistical power rationale was considered rather than relying solely on the 10-times rule. With a significance level of $\alpha = .05$, statistical power of .80, and a medium anticipated effect size ($f^2 = .15$), the obtained sample of 206 participants was considered adequate for estimating the proposed structural relationships.

Table 1. Participant Demographics (n = 206)

Category	Group	n	%
Grade Level	X	80	38.8
	XI	60	29.1
	XII	66	32.0
Gender	Male	48	23.3
	Female	158	76.7

Research Context and Measures

AI-supported mathematics learning was operationalised as the use of AI-based digital tools to support mathematics learning activities, including conceptual explanation, solution checking, generation of alternative strategies, error identification, and revision. The questionnaire contained 18 AI-acceptance items, 8 SRL items, and 5 learning-discipline items, all measured using a five-point Likert-type scale.

The AI acceptance items represented four reflective constructs: PEOU (5 items), PU (5 items), ATU (4 items), and BI (4 items). The SRL construct comprised eight indicators covering planning, monitoring, strategy use, and self-evaluation. Learning discipline was represented by five indicators covering regularity, responsibility, persistence, and consistency in learning behaviour.

Data Analysis

Data were analysed using partial least squares structural equation modelling (PLS-SEM). The analysis consisted of assessments of the reflective measurement model and the structural model. The measurement model was evaluated using outer loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and the heterotrait-monotrait ratio (HTMT). HTMT was used to assess discriminant validity because it is a sensitive criterion in variance-based structural equation modelling (Henseler et al., 2015).

The structural model was evaluated using standardized path coefficients, standard errors, t-values, p-values, bootstrap confidence intervals, R^2 , f^2 , VIF, and direct, indirect, and total effects. Mediation was assessed through the indirect effect and its bootstrap confidence interval, following established procedures for mediation analysis in PLS-SEM (Nitzl et al., 2016). Because the study used cross-sectional self-report data, all relationships are interpreted as structural associations within the proposed model rather than causal effects.

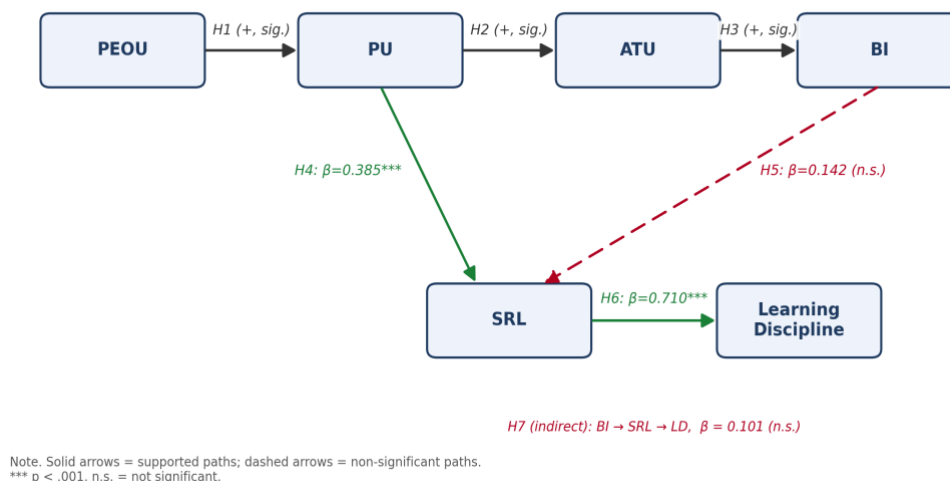


Figure 1. Structural Model with Hypothesized Paths and Standardized Coefficients

RESULTS & DISCUSSION

Results

Descriptive Statistics

Students reported generally positive perceptions of AI-supported mathematics learning. Overall, AI acceptance had a mean of 3.83 on a five-point scale. PU and PEOU were the highest acceptance dimensions, both with $M = 3.92$, followed by ATU ($M = 3.82$). BI had the lowest mean ($M = 3.61$). SRL was relatively high ($M = 4.00$, $SD = .68$), while learning discipline had a mean of 3.70 ($SD = .84$).

Table 2. Descriptive Statistics and Internal Consistency

Construct	Items	M	SD	Cronbach's α
AI acceptance overall	18	3.83	1.10	0.95
PU	5	3.92	0.81	0.86
PEOU	5	3.92	0.86	0.86
ATU	4	3.82	0.88	0.86
BI	4	3.61	0.97	0.87
SRL	8	4.00	0.68	0.85
Learning discipline	5	3.70	0.84	0.86

Among the SRL dimensions, planning was the lowest ($M = 3.72$), whereas monitoring ($M = 4.17$), strategy use ($M = 4.15$), and self-evaluation ($M = 4.23$) were comparatively high.

Reflective Measurement Model

The reflective measurement assessment showed acceptable internal consistency and convergent validity. All Cronbach's alpha values were above .80, composite reliability values exceeded .80, and AVE values exceeded .50. The lowest AVE was observed for SRL (.502), which remained above the conventional .50 criterion.

Table 3. Reflective Measurement Model

Construct	Indicators	Standardized loadings	α	CR	AVE
PU	AI1–AI5	0.809, 0.842, 0.738, 0.863, 0.753	0.858	0.900	0.644
PEOU	AI6–AI10	0.744, 0.817, 0.866, 0.722, 0.833	0.856	0.897	0.637
ATU	AI11–AI14	0.833, 0.881, 0.880, 0.781	0.864	0.908	0.713
BI	AI15–AI18	0.890, 0.876, 0.902, 0.703	0.867	0.909	0.717
SRL	SRL1–SRL8	0.710, 0.723, 0.770, 0.551, 0.640, 0.716, 0.769, 0.762	0.854	0.889	0.502
LD	LD1–LD5	0.779, 0.881, 0.810, 0.814, 0.739	0.864	0.902	0.650

Discriminant Validity

HTMT values were calculated from the indicator-level data. Most construct pairs were below .90; however, the PU–ATU and ATU–BI relationships were comparatively high, with ATU–BI exceeding .90. This pattern is theoretically plausible because these

constructs represent adjacent stages of the partial TAM sequence. The high values should therefore be interpreted transparently rather than concealed.

Table 4. HTMT Matrix

	PU	PEOU	ATU	BI	SRL	LD
PU	—	0.872	0.862	0.775	0.561	0.498
PEOU	0.872	—	0.949	0.891	0.583	0.579
ATU	0.862	0.949	—	0.986	0.597	0.569
BI	0.775	0.891	0.986	—	0.464	0.480
SRL	0.561	0.583	0.597	0.464	—	0.770
LD	0.498	0.579	0.569	0.480	0.770	—

Structural Model

The structural model supported the proposed TAM sequence. PEOU was positively associated with PU ($\beta = .743$, $p < .001$), PU was positively associated with ATU ($\beta = .738$, $p < .001$), and ATU was positively associated with BI ($\beta = .851$, $p < .001$). Beyond the TAM sequence, PU was positively associated with SRL ($\beta = .393$, $p < .001$), whereas BI was not significantly associated with SRL ($\beta = .131$, $p = .195$). SRL was positively associated with learning discipline ($\beta = .593$, $p < .001$), and PU also showed a smaller but significant direct association with learning discipline ($\beta = .140$, $p = .030$).

Table 5. Structural Model Results

Hypothesis	Path	β	SE	t	p	95% CI	f ²	Decision
H1	PEOU → PU	.743	.047	15.853	< .001	[.655, .815]	1.232	Supported
H2	PU → ATU	.738	.047	15.617	< .001	[.646, .813]	1.196	Supported
H3	ATU → BI	.851	.037	23.115	< .001	[.810, .884]	2.619	Supported
H4	PU → SRL	.393	.082	4.811	< .001	[.199, .582]	0.114	Supported
H5	BI → SRL	.131	.082	1.606	.195	[-.056, .317]	0.013	Not supported
H6	SRL → LD	.593	.059	10.014	< .001	[.466, .701]	0.494	Supported

Explained Variance and Collinearity

Table 6. Explained Variance

Endogenous construct	R ²
PU	.552
ATU	.545
BI	.724
SRL	.241
Learning discipline	.452

The model explained 55.2% of the variance in PU, 54.5% in ATU, 72.4% in BI, 24.1% in SRL, and 45.2% in learning discipline. The SRL → learning discipline relationship showed a substantial effect size ($f^2 = .494$), whereas BI → SRL had a very small effect size ($f^2 = .013$).

Table 7. Inner VIF

Endogenous construct	Predictor	VIF
PU	PEOU	1.000
ATU	PU	1.000
BI	ATU	1.000
SRL	PU	2.659
SRL	BI	2.659
LD	SRL	1.315
LD	PU	1.315

All VIF values were below commonly used thresholds, indicating that structural collinearity was not a serious concern.

Mediation Analysis

The primary mediation analysis examined whether SRL mediated the relationship between PU and learning discipline. The indirect effect was statistically significant ($\beta = .233$, 95% CI [.115, .348], $p < .001$). The direct effect of PU on learning discipline remained significant ($\beta = .140$, $p = .030$), and the total effect was $\beta = .374$. Because both the direct and indirect effects were significant, the result supports partial mediation.

Table 8. Mediation Analysis

Effect	β	p	95% CI	Interpretation
Direct PU $\rightarrow$ LD	.140	.030	[.013, .281]	Significant
Indirect PU $\rightarrow$ SRL $\rightarrow$ LD	.233	< .001	[.115, .348]	Significant
Total PU $\rightarrow$ LD	.374	—	—	Significant
Mediation	—	—	—	Partial mediation

Discussion

The findings refine the role of technology acceptance in AI-supported mathematics learning. The supported TAM sequence indicates that students who perceived AI as easier to use also tended to perceive it as more useful, develop more favourable attitudes, and report stronger behavioural intentions. This pattern is consistent with the basic logic of TAM and suggests that conventional technology-acceptance relationships remain relevant in AI-supported mathematics learning. However, the more educationally relevant finding emerged beyond behavioural intention. PU was significantly associated with SRL, whereas BI was not. This distinction suggests that students' willingness to use AI does not necessarily correspond to how they regulate their mathematics learning. A student may be willing to use AI because it is accessible, convenient, or interesting, without necessarily using it for planning, monitoring, strategy selection, or self-evaluation.

By contrast, perceived usefulness is conceptually closer to the learning activities that AI may support. Students who perceive AI as useful for understanding mathematical concepts, checking procedures, comparing strategies, identifying errors, and revising their work may be more likely to incorporate the technology into their active learning. Recent research on AI-supported learning similarly emphasises that AI can support learning regulation when embedded in meaningful learning activities rather than merely treated as an answer-generating mechanism (Järvelä et al., 2023; Jin et al., 2023; Lan & Zhou, 2025).

The non-significant BI-SRL relationship should nevertheless be interpreted cautiously. This finding does not mean that behavioural intention is inherently irrelevant to

learning. Rather, in this sample and structural model, intention was not significantly associated with SRL after accounting for PU. One possible explanation is that intention reflects willingness or readiness to use AI but does not capture the quality or purpose of actual use. This interpretation is especially relevant in mathematics. AI can be used as cognitive support, such as to request explanations, examine intermediate procedures, compare strategies, or identify errors, or primarily to obtain final answers. Bastani et al. (2025) demonstrated that unrestricted use of generative AI in high school mathematics can pose learning risks when students rely on the technology as a substitute for independent problem-solving. The present study complements this evidence by showing that intention to use AI was not itself significantly associated with SRL. Considering that the present study employed a cross-sectional survey and self-reported measures, these interpretations remain tentative. The study did not collect AI-use logs, screen activity, classroom observations, interviews, or think-aloud protocols. Therefore, the data cannot establish whether perceived usefulness leads students to change their learning behaviour. The findings should instead be interpreted as structural associations within the proposed model.

The significant SRL-learning discipline relationship provides an important educational dimension. Students reporting stronger self-regulated learning also reported more disciplined learning behaviour. The finding is theoretically coherent because SRL involves planning, monitoring, regulation, and evaluation, whereas learning discipline concerns consistency and responsibility in maintaining learning activities. In mathematics, this relationship is particularly plausible. Mathematical learning requires sustained effort, sequential reasoning, error checking, and revision. Students who monitor their progress and evaluate their performance may be better positioned to maintain study routines, complete tasks, persist through difficulties, and adjust their strategies.

The mediation analysis provides further support for positioning SRL as a learning-process bridge between perceived AI usefulness and learning discipline. The indirect effect of PU on learning discipline through SRL was significant, while the direct PU-LD association remained significant. This pattern indicates partial mediation. Thus, perceived usefulness was associated with learning discipline through SRL while also retaining a direct association with learning discipline. The mediation finding extends the conventional interpretation of TAM in educational contexts. Classical TAM primarily seeks to explain technology acceptance and behavioural intention. The present model instead examines what lies beyond intention. Incorporating SRL and learning discipline shifts the analytical focus from whether students intend to use AI to how technology acceptance relates to learning processes and behavioural consistency. The result should not be interpreted as evidence that PU is a decisive mechanism. Rather, PU emerged as a particularly important construct in the proposed model because it was significantly associated with SRL and was part of a significant indirect pathway to learning discipline.

The model explained 45.2% of the variance in learning discipline. This indicates that the proposed predictors provide a meaningful basis for understanding disciplined learning behaviour in this sample, while also demonstrating that substantial variance remains unexplained. Other factors, including motivation, teacher support, classroom climate, workload, academic goals, and prior learning habits, likely influence learning discipline. The proposed model should therefore be understood as one explanatory framework rather than a comprehensive model of all determinants of learning discipline. The findings also contribute to the emerging literature on responsible and human-centred AI in education. Recent scholarship has emphasised that the educational value of AI depends on how AI is integrated into learning activities and how learners interact with the technology (Zhu et al., 2025). The present findings support this perspective by indicating

that perceived usefulness is more closely associated with SRL than behavioural intention in the proposed model.

From a practical perspective, mathematics teachers should design AI-supported activities around purposeful learning functions. Students can be required to request conceptual explanations, compare alternative solution strategies, verify intermediate steps, identify potential errors, explain why a solution is valid, revise their own work, and reflect on what they learned from the interaction. Such activities may help position AI as a cognitive and metacognitive support rather than a replacement for students' mathematical reasoning.

Limitations and Future Research

This study used a cross-sectional survey design. Consequently, the structural relationships should not be interpreted as causal effects. Longitudinal or experimental studies are needed to determine whether changes in perceived AI usefulness in SRL and learning discipline follow. All principal constructs were measured using self-report data. The study therefore captures students' perceptions and reported behaviours rather than objectively observed AI-use behaviour. Future research should integrate AI-use logs, learning analytics, interviews, classroom observations, or think-aloud protocols.

The study used convenience sampling, and the participating schools were drawn from four provinces in Java. The results therefore provide contextual evidence rather than nationally representative estimates. The sample was also disproportionately female, which should be considered when interpreting generalisability. Some TAM constructs showed relatively high HTMT values in the indicator-level diagnostic, particularly PU–ATU and ATU–BI. Future research should examine whether higher-order acceptance models or alternative measurement specifications better represent these closely related constructs.

Future studies could also incorporate mathematics achievement as an additional outcome. Doing so would allow researchers to examine whether the pathway from AI acceptance through SRL and learning discipline is associated with measurable mathematical learning outcomes over time.

CONCLUSION

This study found that students reported generally positive perceptions of AI-supported mathematics learning, while the educational significance of AI acceptance extended beyond behavioural intention. Within the proposed model, perceived usefulness emerged as a particularly important construct because it was positively associated with self-regulated learning, whereas behavioural intention was not significantly associated with SRL. Self-regulated learning was also positively associated with learning discipline, and perceived usefulness showed both direct and indirect associations with learning discipline through SRL. The significant indirect association supports the role of SRL as a learning-process pathway linking perceived usefulness with learning discipline. However, these relationships should be interpreted as structural associations rather than causal effects given the cross-sectional survey design.

The findings suggest that AI-supported mathematics learning may be more educationally meaningful when students perceive AI as useful for specific learning activities, such as understanding mathematical concepts, checking solution procedures, identifying errors, and reflecting on their learning strategies. Accordingly, schools and

mathematics teachers should focus not simply on encouraging AI use, but on designing purposeful AI-supported learning activities that encourage students to plan, monitor, regulate, and evaluate their own mathematical learning. Such an approach can position AI as a support for students' self-regulated learning while maintaining students' responsibility for their learning processes and disciplined study behaviour.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AI USAGE DECLARATION

The author declares that ChatGPT and NotionAI were used only for grammar revision and paraphrasing to improve the readability of this article. The author is fully responsible for the substance and accuracy of the content produced.

REFERENCES

- Bastani, H., Bastani, O., Sungu, A., Ge, H., Kabakcı, Ö., & Mariman, R. (2025). Generative AI without guardrails can harm learning: Evidence from high school mathematics. *Proceedings of the National Academy of Sciences*, 122(26), e2422633122. <https://doi.org/10.1073/pnas.2422633122>
- Crompton, H. & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education*, 20, 22. <https://doi.org/10.1186/s41239-023-00392-8>
- Dai, W., Li, Z., & Jia, N. (2022). Self-regulated learning, online mathematics learning engagement, and perceived academic control among Chinese junior high school students during the COVID-19 pandemic: A latent profile analysis and mediation analysis. *Frontiers in Psychology*, 13, 1042843. <https://doi.org/10.3389/fpsyg.2022.1042843>
- 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>
- Gabriel, F., Kennedy, J. P., Marrone, R., & Leonard, S. (2025). Pragmatic AI in education and its role in mathematics learning and teaching. *npj Science of Learning*, 10, 26. <https://doi.org/10.1038/s41539-025-00315-4>
- 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>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43, 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Järvelä, S., Nguyen, A., & Hadwin, A. F. (2023). Human and artificial intelligence collaboration for socially shared regulation in learning. *British Journal of Educational Technology*, 54(5), 1057–1076. <https://doi.org/10.1111/bjet.13325>

- Jin, S. H., Im, K., Yoo, M., Roll, I., & Seo, K. (2023). Supporting students' self-regulated learning in online learning using artificial intelligence applications. *International Journal of Educational Technology in Higher Education*, 20, 37. <https://doi.org/10.1186/s41239-023-00406-5>
- Kuo, B.-C., Bai, Z.-E., & Lin, C.-H. (2026). Developing an AI learning companion for mathematics problem-solving in elementary schools. *Computers & Education*, 240, 105463. <https://doi.org/10.1016/j.compedu.2025.105463>
- Lan, M. & Zhou, X. (2025). A qualitative systematic review on AI empowered self-regulated learning in higher education. *npj Science of Learning*, 10, 21. <https://doi.org/10.1038/s41539-025-00319-0>
- Nitzl, C., Roldán, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling. *Industrial Management & Data Systems*, 116(9), 1849–1864. <https://doi.org/10.1108/IMDS-07-2015-0302>
- Ouyang, F., Zheng, L., & Jiao, P. (2022). Artificial intelligence in online higher education: A systematic review of empirical research from 2011–2020. *Education and Information Technologies*, 27, 7893–7925. <https://doi.org/10.1007/s10639-022-10925-9>
- Venkatesh, V. & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- Zimmerman, B. J. (1989). A social cognitive view of self-regulated academic learning. *Journal of Educational Psychology*, 81(3), 329–339. <https://doi.org/10.1037/0022-0663.81.3.329>
- Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice*, 41(2), 64–70. https://doi.org/10.1207/S15430421TIP4102_2
- Zhu, H., Sun, Y., & Yang, J. (2025). Towards responsible artificial intelligence in education: A systematic review on identifying and mitigating ethical risks. *Humanities and Social Sciences Communications*, 12, 1111. <https://doi.org/10.1057/s41599-025-05252-6>