Enhancing Calculus Learning Outcomes for Engineering Students through the ADAB Framework and AI Tools

Nor Kamariah Kasmin@Bajuri[1*], Nur Idayu Alimon[1], Nurhazirah Mohamad Yunos[1], Wan Munirah Wan Mohamad[1], Nur Syamilah Arifin[1]

[1]Fakulti Sains Komputer dan Matematik,, Universiti Teknologi MARA Cawangan Johor, Kampus Pasir Gudang, 81750 Masai, Johor, Malaysia.

***Corresponding Author**

DOI: https://dx.doi.org/10.47772/IJRISS.2026.100800028

Received: 09 August 2026; Accepted: 14 August 2026; Published: 25 August 2026

ABSTRACT

Mastering calculus is vital for engineering students, yet many struggle due to inadequate basic mathematical knowledge. Weaknesses in mastering the theory and basic concepts of mathematics significantly hinder calculus learning outcomes, as evidenced by a clear positive relationship between basic mathematics proficiency and calculus achievement. Common failure factors include an inability to understand question requirements or translate them into appropriate calculations, alongside fundamental conceptual gaps that negatively impact topics like differentiation. To address these challenges, this study explores an innovative pedagogical intervention combining the ADAB framework with AI-assisted learning technologies like NotebookLM. The primary objective is to evaluate how integrating structured frameworks and AI tools can minimize conceptual errors, bridge foundational gaps, and improve overall performance in calculus courses. The methodology implements a blended learning design utilizing the ADAB framework to structure student engagement, supported by NotebookLM to provide personalized, interactive guidance and targeted practice on complex calculus topics. Preliminary findings indicate that integrating these AI-driven tools enhances students' comprehension of mathematical rules and significantly reduces procedural errors. Ultimately, these results demonstrate that combining structured pedagogical frameworks with modern AI technologies can transform calculus education, offering educators scalable strategies to cultivate deeper analytical skills and support academic success across engineering disciplines.

Keywords: Mathematics anxiety, ADAB framework, AI tools, blended learning, mathematics education.

INTRODUCTION

Mathematics anxiety is a widespread issue in modern engineering education that directly impacts student success, academic performance, and retention rates in higher education. Many engineering undergraduates view their core mathematics course which is Calculus, not as an essential foundational tool for their discipline, but as a major academic burden. This negative perception creates a damaging psychological and academic cycle. According to the control-value theory of achievement emotions, when students perceive low personal competence in executing mathematical tasks while simultaneously valuing academic success highly, it leads to severe emotional distress that actively impairs their cognitive performance (Pekrun et al., 2025). Because engineering curriculum are heavily cumulative, these poor math results do not remain isolated; they directly damage student performance in core downstream engineering subjects like mechanics, thermodynamics, and electrical circuits. Concurrently, traditional abstract teaching methods often cause cognitive overload in dense STEM tracks. Recent meta-analyses confirm a moderate but consistent negative correlation between mathematics anxiety and mathematics achievement, particularly inside highly competitive, exam-oriented educational systems (Zhao and Wang, 2026). Under these conditions, students quickly lose interest in the subject matter and find it increasingly difficult to understand complex mathematical rules, integration techniques, and calculus formulas. To address this critical issue, educators require active learning strategies that simultaneously address both the cognitive and emotional aspects of the classroom environment (Taylor and Evans, 2025). Visual learning tools and source-grounded artificial intelligence (AI) frameworks have emerged as promising mechanisms to build clearer mental frameworks, scaffold dense information, and foster learner autonomy (Robinson et al., 2026). This paper investigates how integrating NotebookLM, an advanced AI-powered learning platform, into the study process simplifies complex information, optimizes cognitive processing, and reduces mathematical anxiety among engineering students taking Calculus. (Smith and Peterson, 2025).

LITERATURE REVIEW

The integration of AI within tertiary STEM pedagogy requires a thorough understanding of the relationship between mathematical cognitive, emotional performance, and structural educational frameworks. This section reviews current research on mathematics anxiety in engineering curricula, the cognitive benefits of visual mapping, and the operational application of source-grounded Retrieval-Augmented Generation (RAG) platforms within structured learning designs.

Mathematics Anxiety and Achievement Outcomes in Engineering Education

Mathematics anxiety represents a significant academic barrier in undergraduate engineering tracks, where mathematical competency is required for technical advancement. Undergraduates frequently view core courses such as Calculus as substantial academic hurdles rather than supportive operational tools. This disconnect is explained by the control-value theory of achievement emotions, which posits that a student's affective state during an evaluative task is directly tied to their perceived control over the task and the subjective value they assign to the outcome (Pekrun et al., 2025). When students place a high value on academic success but perceive their own skills as inadequate, they experience severe performance anxiety. Because engineering tracks are inherently cumulative, early conceptual failures in abstract math courses propagate downstream. Unresolved mathematics anxiety directly undermines student achievement in advanced applied fields, including structural mechanics, thermodynamics, fluid dynamics, and electrical circuit analysis. Recent systematic reviews spanning a decade of education data confirm a stable, statistically significant negative correlation between high math anxiety and poor academic achievement, particularly inside exam-oriented institutional structures that emphasize memorization over comprehension (Zhao and Wang, 2026). Consequently, engineering tracks require active pedagogical interventions that ease working memory constraints and lower emotional barriers.

Cognitive Load Optimization via Visual Scaffolding

Traditional pedagogical approaches in engineering mathematics often rely on abstract, formula presentations that can induce high cognitive load. Cognitive load theory indicates that working memory has a limited capacity when processing complex, unfamiliar data. When instructional methods over-rely on dense, linear text and disconnected algebraic rules, students quickly lose interest and struggle to organize essential integration formulas, Calculus rules, and geometric relationships. To mitigate instructional friction, educational researchers emphasize the value of active learning strategies that merge cognitive restructuring with emotional support mechanisms (Taylor and Evans, 2025). Visual mapping tools, such as hierarchical mind maps and infographics, serve as external cognitive scaffolds. By translating dense textbook chapters into interconnected visual blocks, mind mapping enables students to build clear mental models and see how distinct mathematical rules relate to one another. This spatial organization reduces extraneous cognitive load, letting working memory focus on strategic problem-solving and deep conceptual processing rather than basic information retrieval (Sobel and Sarmiento, 2025).

Source-Grounded AI and Retrieval-Augmented Generation (RAG) in STEM

While generative AI applications have expanded rapidly in higher education, standard Large Language Models (LLMs) present challenges when used as direct tutoring aids due to their tendency to generate factual errors or "hallucinations". In highly precise fields like engineering mathematics, any deviation from absolute structural accuracy undermines a tool's educational utility and threatens academic integrity. This constraint has led to a shift toward source-grounded AI tools that employ Retrieval-Augmented Generation (RAG) architectures, such as NotebookLM (Salinas Frencia, 2025).A RAG configuration restricts the AI's generative engine to a closed corpus of user-uploaded source materials, ensuring that all summaries, mind maps, and explanations remain mathematically accurate and aligned with the assigned syllabus (Robinson et al., 2026). When integrated into engineering tracks, source-grounded AI tools function as reliable cognitive aids that reduce study time and provide clear visual structures without generating misleading data (Smith and Peterson, 2025). This technology supports student autonomy by acting as an interactive, customized tutor that bridges abstract theory and practical problem-solving.

The ADAB Framework as a Structural Blueprint for Active Learning

The introduction of AI tools into technical classrooms must be guided by structured pedagogical frameworks to prevent passive reliance on technology and maintain student engagement. The institutional ADAB framework provides a systematic, seven-element learning design (Situate, Digest, Synthesize, Create, Connect, Reflect, and Value and Extend) that guides students through an active learning sequence. Prior research indicates that forcing students to manually execute the initial stages such as reading text (Digest) and writing summaries in their own words (Synthesize). This is essential to build a solid foundational understanding before engaging with digital tools (Robinson et al., 2026). The subsequent pairing of these human-generated summaries with AI visual tools (Create, Connect) ensures that technology serves as an optimization tool rather than a replacement for critical thinking. By embedding AI workflows within the ADAB framework, educators can maintain rigorous academic standards while providing students with scalable strategies to manage anxiety and complete complex engineering coursework (Uzun and Hoxha, 2026). anxiety is defined as a state of tension and fear that interferes with number manipulation and mathematical problem solving. It may stem from negative classroom experiences, high parental or societal expectations, and the stereotype that mathematics is inherently difficult. Serin (2023) identified cultural perceptions and educational practices such as time-pressured tests and rigid assessment systems. These considered as contributors to heightened anxiety levels.

This anxiety has been shown to impair working memory and attention, disrupt information processing, and reduce persistence in challenging tasks. Students with persistent mathematics anxiety often adopt fixed mindsets, believing that mathematical ability is innate and unchangeable. Over time, this mindset reinforces avoidance behaviours and reduces opportunities for practice, creating a self-perpetuating cycle of fear and underachievement.

METHODOLOGY

This study utilizes a structured, four-phase action research methodology mapped across the institutional ADAB learning design framework which includes eight elements: Situate, Digest, Synthesize, Create, Connect, Reflect, Value and Extend. The intervention is designed to actively engage students in their own learning process while using AI for structural organization as shown in Fig. 1 below. Following the intervention, students completed the questionnaire to reflect on their learning experiences and perceptions of the AI-assisted learning process.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VIII August 2026

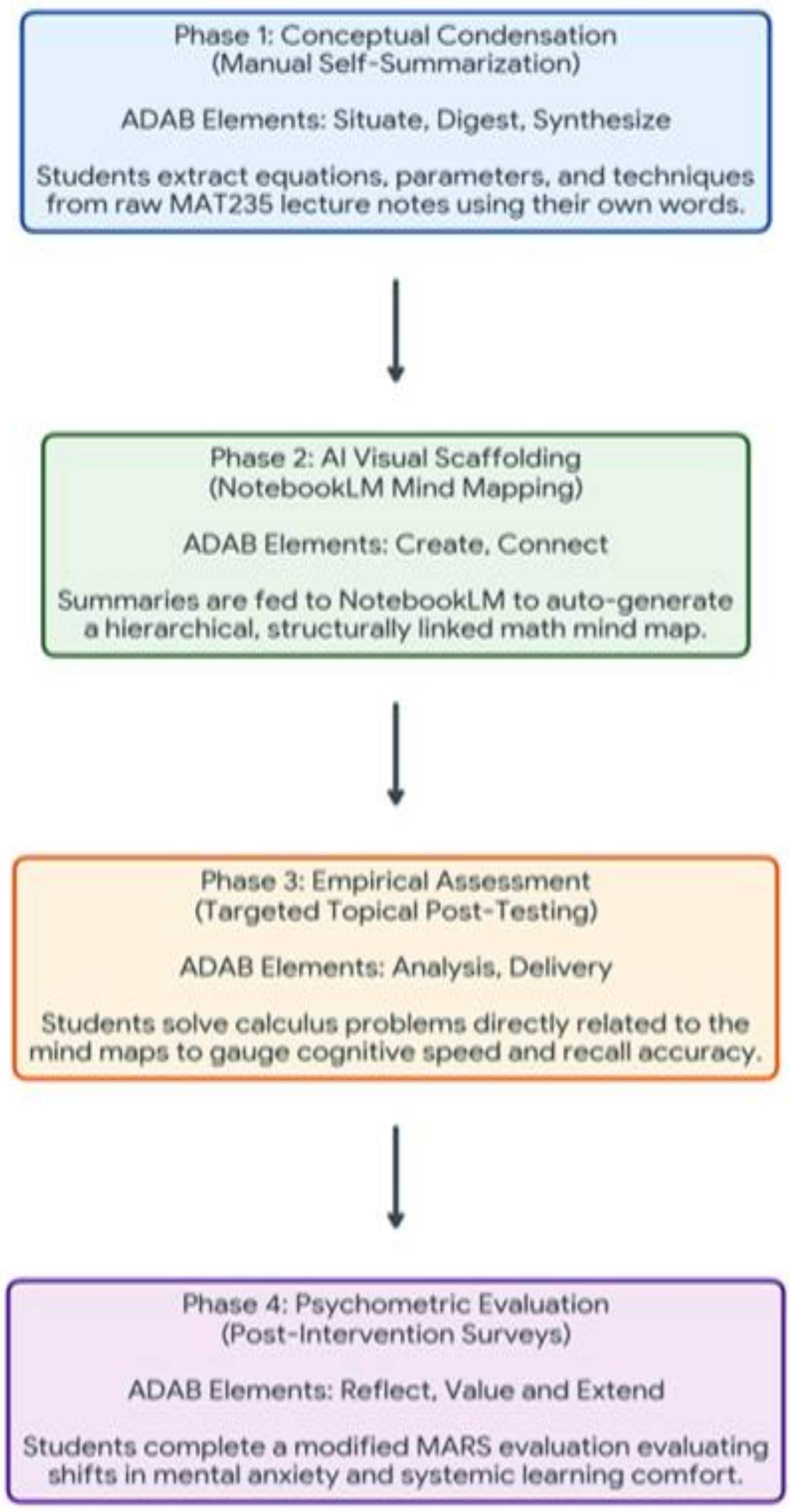

Fig. 1 A learning process for Calculus learning

Phase 1: Conceptual Condensation (Situate, Digest, Synthesize)

The intervention initiated with independent note synthesis, deeply rooted in the Situate and Digest elements of the ADAB model. Students began by analyzing their raw lecture notes for specific, focusing primarily on Methods of Integration (such as Integration by Parts and Trigonometric Substitutions) as shown in Fig. 2.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VIII August 2026

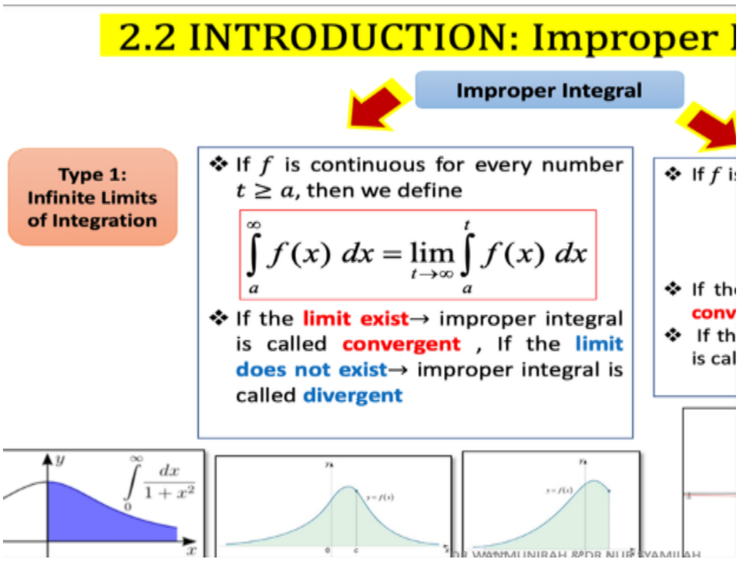

Fig. 2 The raw lecture notes obtained from the lecturers

Before interacting with any external technology or AI interface, participants were required to fulfill the Synthesize element. They manually processed the mathematical information and wrote out a concise summary in their own words. This phase forced students to manually work through core Calculus theories, integration equations, and operational steps, aligning with self-regulated learning theories to prevent passive reliance on technology and counter automated superficial copying. The student's note as shown in Fig 3.

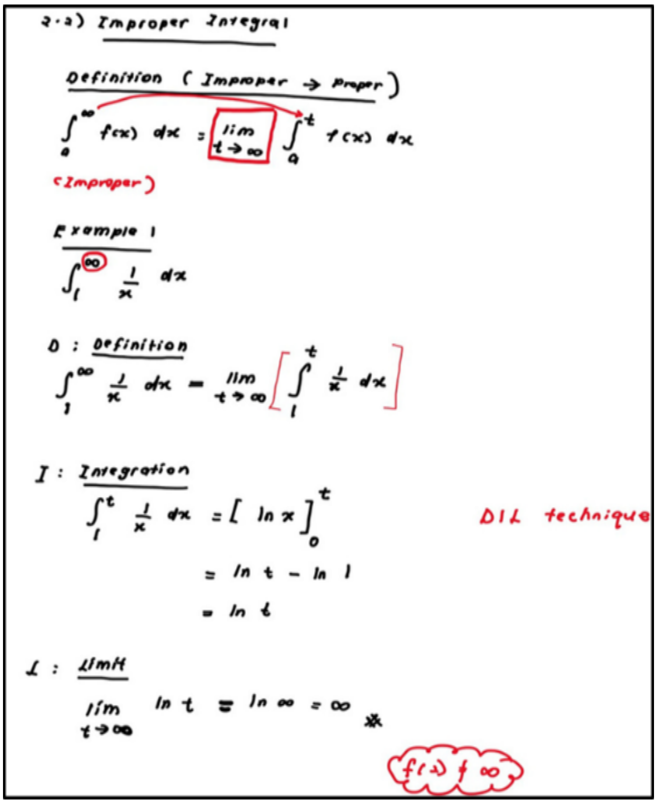

Fig. 3 Students' note

Phase 2: AI Visual Scaffolding (Create, Connect)

In the second phase, students transitioned to the Create and Connect elements of the framework. The student-generated text summaries from Phase 1 were uploaded as primary source documents into the NotebookLM platform. Students then prompted the AI platform to organize their personal summaries into structured,

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VIII August 2026

hierarchical mind maps. This step leveraged the software's native visual formatting features to link different integration formulas, trigonometric identities, and boundary conditions. This process created a clear visual architecture of the chapter, helping students bridge the gap between abstract algebraic rules and practical engineering applications. The infographic result from NotebookLM is shown in Fig 4.

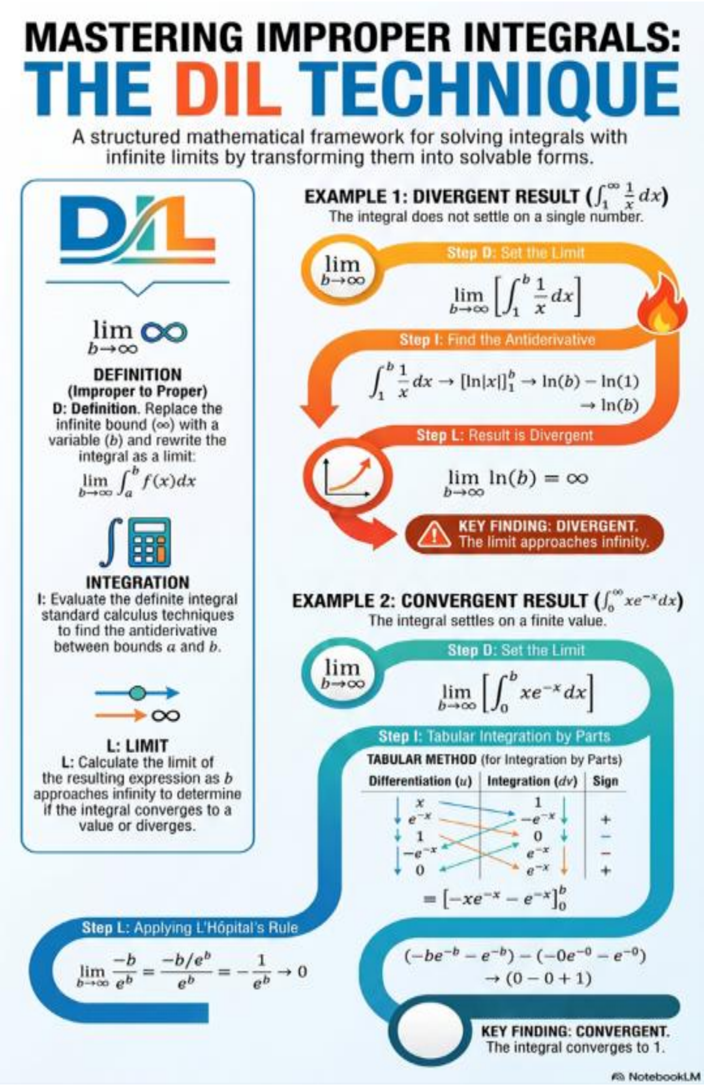

Fig. 4 Example of infographic produced from NotebookLM

Phase 3: Empirical Assessment (Analysis, Delivery)

To verify the academic and cognitive value of the generated mind maps, students entered the Analysis and Delivery stages. Participants were subjected to targeted topical post-tests featuring complex in Calculus problems directly related to the mind-mapped chapters. This testing phase measured whether the visual scaffolds translated into better problem-solving abilities, improved calculation speed, and better factual retention under exam conditions, serving as a primary direct metric for mathematical efficiency and conceptual mastery.

Phase 4: Evaluation (Reflect, Value and Extend)

The final phase incorporated the Reflect, Value and Extend elements of the ADAB framework. Students completed a structured questionnaire to evaluate their experiences with the learning intervention. The questionnaire consisted of five sections:

- Section A: Calculus Learning Outcome – evaluated students' perceived learning outcomes and understanding of the selected Calculus topics.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VIII August 2026

- Section B: ADAB Framework – evaluated students' perceptions of the learning process based on the ADAB framework.
- Section C: AI/NotebookLM Implementation – examined students' perceptions of the use of AI and NotebookLM in supporting their learning and organizing mathematical information.
- Section D: Mathematics Anxiety – examined students' perceived mathematics anxiety during the learning process.
- Section E: Revision and Learning Autonomy – evaluated students' perceptions of revision efficiency, confidence, independent learning and learning autonomy.

The questionnaire employed a Likert-scale response format. This quantitative study was conducted to investigate students' learning outcomes, perceptions of the ADAB learning frameworks, AI-assisted learning through NotebookLM, mathematics anxiety, and learning autonomy in Calculus learning. A total of 44 students participated in the study and were selected using a convenience sampling technique from several engineering classes in Semester 2 at a public university in Malaysia. The intervention was conducted over a period of fourteen weeks which covered all chapters in a Calculus course.

Data Analysis

The questionnaire data were analyzed quantitatively using Statistical Package for the Social Sciences (SPSS). The Pearson product-moment correlation analysis was conducted to examine the relationships between Calculus learning outcomes, the ADAB framework, AI/NotebookLM implementation, mathematics anxiety, revision and learning autonomy, and overall perceived effectiveness of the intervention.

RESULT AND DISCUSSIONS

To examine the relationships among the key variables in the study, a Pearson product-moment correlation analysis was conducted. The results, presented in Tab. 1, indicate the strength, direction, and statistical significance of the associations among Calculus Learning Outcomes, the ADAB Framework, AI/NotebookLM Implementation, Mathematics Anxiety, Revision and Learning Autonomy, and Overall Effectiveness.

Correlations

		Calculus Learning Outcomes	ADAB Framework	AI/Notebook LM Implementation	Mathematics Anxiety	Revision and Learning Autonomy	Overall Effectivenes
Calculus Learning Outcomes	Pearson Correlation	1	.729**	.634**	.123	.727**	.648**
	Sig. (2-tailed)		<.001	<.001	.427	<.001	<.001
	N	44	44	44	44	44	44
ADAB Framework	Pearson Correlation	.729**	1	.624**	.327*	.760**	.794**
	Sig. (2-tailed)	<.001		<.001	.030	<.001	<.001
	N	44	44	44	44	44	44
AI/NotebookLM Implementation	Pearson Correlation	.634**	.624**	1	.343*	.780**	.772**
	Sig. (2-tailed)	<.001	<.001		.023	<.001	<.001
	N	44	44	44	44	44	44
Mathematics Anxiety	Pearson Correlation	.123	.327*	.343*	1	.324*	.286
	Sig. (2-tailed)	.427	.030	.023		.032	.060
	N	44	44	44	44	44	44
Revision and Learning Autonomy	Pearson Correlation	.727**	.760**	.780**	.324*	1	.859**
	Sig. (2-tailed)	<.001	<.001	<.001	.032		<.001
	N	44	44	44	44	44	44
Overall Effectivenes	Pearson Correlation	.648**	.794**	.772**	.286	.859**	1
	Sig. (2-tailed)	<.001	<.001	<.001	.060	<.001	
	N	44	44	44	44	44	44

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Tab. 1 Pearson Correlations among Calculus Learning Outcomes, ADAB Framework, AI/NotebookLM Implementation, Mathematics Anxiety, Revision and Learning Autonomy, and Overall Effectiveness

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VIII August 2026

Calculus Learning Outcomes and Their Associations with Other Variables

The questionnaire findings provided further insight into students' perceived Calculus learning outcomes following the intervention. The results showed a strong positive correlation between the ADAB Framework and Calculus Learning Outcomes ($r = .729$, $p < .001$). Similarly, AI/NotebookLM Implementation demonstrated a strong positive correlation with Calculus Learning Outcomes ($r = .634$, $p < .001$). In the same vein, Revision and Learning Autonomy demonstrated a strong positive relationship with Calculus Learning Outcomes ($r = .727$, $p < .001$), indicating that students who reported more effective revision and greater learning autonomy also tended to report more positive Calculus learning outcomes. These findings indicate that students who perceived the ADAB learning process and AI-assisted learning implementation more positively also tended to report more positive Calculus learning outcomes.

Relationships Among the Learning Components

The Pearson correlation analysis revealed significant positive relationships among the major components of the proposed learning approach. The ADAB Framework was strongly correlated with AI/NotebookLM Implementation ($r=.624$, $p< .001$), suggesting that students who perceived the structured ADAB learning process positively also tended to perceive the integration of NotebookLM positively.

Similarly, the ADAB Framework also demonstrated a strong positive relationship with Revision and Learning Autonomy ($r = .760$, $p < .001$). Likewise, AI/NotebookLM Implementation was strongly correlated with Revision and Learning Autonomy ($r = .780$, $p < .001$). These findings suggest that the structured learning process and AI-supported visual organization may complement students' revision practices and perceptions of independent learning.

Taken together, these findings demonstrate that the three learning components, which are structured learning through the ADAB framework, AI-assisted learning through NotebookLM, and students' revision and learning autonomy, where they were closely interconnected. The findings suggest that the AI-assisted approach did not function independently of the pedagogical framework; rather, the structured learning process and AI-supported organization of learning materials were associated with students' perceptions of their ability to revise and manage their learning more independently.

Mathematics Anxiety and Its Relationships with Other Variables

In contrast to the other variables, Mathematics Anxiety did not demonstrate a significant relationship with Calculus Learning Outcomes ($r = .123$, $p = .427$). This indicates that students' reported levels of mathematics anxiety were not significantly associated with their perceived Calculus learning outcomes in the present sample.

Mathematics Anxiety showed weak positive correlations with the ADAB Framework ($r = .327$, $p = .030$), AI/NotebookLM Implementation ($r = .343$, $p = .023$), and Revision and Learning Autonomy ($r = .324$, $p = .032$). Although these relationships were statistically significant, their relatively weak strength suggests that the associations should be interpreted cautiously.

The fact that the questionnaire only collected data regarding how students perceived their anxiety about mathematics after the intervention and did not collect any data before the intervention, means that it is impossible to conclude from these results that students experienced less anxiety related to math. Rather, these results showed a correlation between what students thought their anxiety was like with regards to mathematics after the intervention and the various aspects of their learning method. Studies conducted in the future could use a pre/post-test design to see if there is any change in the level of anxiety students experience with regards to math over time using AI-assisted visual learning.

Overall Effectiveness of the AI-Assisted ADAB Learning Approach

The analysis further examined the relationships between the key learning components and students' perceptions of the overall effectiveness of the proposed learning approach. The ADAB Framework demonstrated a strong positive correlation with Overall Effectiveness ($r = .794$, $p < .001$), while AI/NotebookLM Implementation also showed a strong positive relationship with Overall Effectiveness ($r = .772$, $p < .001$). These findings indicate that students who perceived the ADAB learning process and AI-assisted implementation more positively were also more likely to perceive the overall learning approach as effective.

The strongest correlation in the analysis was observed between Revision and Learning Autonomy and Overall Effectiveness ($r = .859$, $p < .001$). This finding suggests that students' perceptions of effective revision and greater autonomy were particularly closely associated with their overall perception of the learning approach. The strong relationship may indicate that students valued the ability to independently review, organize, and manage their learning as an important aspect of the intervention.

Overall, the findings indicate that the effectiveness of the proposed learning approach was positively associated with its three major components: the structured ADAB learning process, AI-assisted learning through NotebookLM, and students' revision and learning autonomy.

CONCLUSIONS

The use of an ADAB-based learning framework combined with AI assistance via NotebookLM was investigated to enhance students' learning experiences in Calculus. In this approach, students were encouraged to independently organize and synthesize mathematical concepts prior to being provided with AI-based tools that would allow them to visualize and/or organize their learning materials. The findings showed positive associations among the ADAB framework, AI/NotebookLM implementation, Calculus learning outcomes, revision and learning autonomy, and the overall effectiveness of the learning approach. The results also suggest that AI-generated visual materials can support students in understanding, organizing, and revising mathematical concepts while promoting independent learning. Overall, the study highlights the potential of combining a structured learning framework with AI-assisted learning, with AI serving as a supporting tool rather than replacing students’ own mathematical thinking.

ACKNOWLEDGMENT

The authors express their gratitude for the strong support of Universiti Teknologi MARA Cawangan Johor Kampus Pasir Gudang in conducting this research.

REFERENCES

1. Pekrun, R., Stephens, E. J., & Fraser, J. (2025). Impact of math anxiety and general anxiety on academic achievement: An integration of control-value theory and stress models. Journal of Educational Psychology, 117(2), 210–224.
2. Robinson, T., Shoitan, M., Molina, R., & Medina, A. (2026). Source-grounded AI and learner autonomy in higher education: A NotebookLM case study. Journal of Artificial Intelligence in Education, 14(3), 89–104.
3. Salinas Frencia, J. (2025). NotebookLM: An LLM with RAG for active learning and collaborative tutoring in STEM. ResearchGate Preprint, doi:10.13140/RG.2.2.39077.2640.
4. Smith, K., & Peterson, L. (2025). Transforming STEM education: A case study on the pedagogical implementation of Google's NotebookLM. International Journal of EdTech Innovation, 8(4), 312–327.
5. Sobel, M., & Sarmiento, L. (2025). Mathematical anxiety’s mediating significance in the relationship between self-efficacy and mathematical efficiency. International Journal of Research and Innovation in Social Science, 9(8), 1142–1155.

6. Taylor, H., & Evans, M. (2025). Understanding mathematics anxiety: The role of social-emotional skills and perceived lesson quality. Cogent Education, 12(1), 2609386.
7. Uzun, A., & Hoxha, B. (2026). Latent profiles of perfectionism and mathematics anxiety among university students. Higher Education Research & Development, 45(4), 712–729.
8. Zhao, Y., & Wang, L. (2026). Mathematics anxiety and its impact on students' learning outcomes: A comprehensive meta-analysis review (2014–2024). Educational Review, 78(1), 45–62.