AI-Supported Tutoring and Cognitive Learning Styles in an Engineering Mathematics Refresher Course

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Abstract

Many second-year engineering students enter advanced mathematics courses with gaps in foundational knowledge, leading to high failure rates and limited progression in engineering studies. Artificial intelligence (AI)-driven tutoring has emerged as a potential intervention to address these gaps by providing structured support and real-time feedback. This study investigates the effectiveness of AI-supported tutoring in a one-week intensive refresher course, with a focus on how cognitive learning styles influence engagement.

Using Neethling Brain Instrument (NBI) cognitive profiling, Google Form surveys, and interaction data from the Mindjoy tutorbot, the analysis revealed that students with structured, analytical preferences (L1) engaged most frequently with the AI tutor, while creative (R1) and relational (R2) students engaged less. Students who made frequent use of the AI tutor reported increased confidence in problem-solving. These findings highlight the need for AI tutoring systems to adapt to diverse cognitive profiles to maximise engagement and learning outcomes.

Keywords: AI tutoring, engineering education, mathematics refresher course, cognitive profiles, student engagement

1 Introduction

Artificial intelligence (AI) tools are increasingly used in education to personalise learning, provide real-time feedback, and support complex problem-solving (Green & Carter, 2022). While AI has been applied successfully in adaptive learning platforms, automated grading, and intelligent tutoring systems, its role in short, intensive refresher courses remains underexplored.

Mathematics proficiency is essential for engineering students, yet many enter second-year courses with foundational gaps that hinder their ability to master advanced concepts (Bringula et al., 2021). At North-West University (NWU), high failure rates in early-year mathematics modules have prompted the introduction of a one-week pre-semester refresher course aimed at strengthening conceptual understanding before formal classes begin.

This study examines whether AI-supported tutoring can enhance engagement and learning outcomes in this setting. The Mindjoy large language model (LLM) tutorbot was integrated into the course to provide content review, guided problem-solving, and clarification of key concepts (Mindjoy, 2025). Unlike traditional instruction, the AI tutor offered instant, personalised feedback and self-paced learning opportunities.

The research addressed three questions:

1. How does student engagement with AI tutors vary across cognitive learning styles?
2. How effective is AI in addressing common misconceptions in mathematics?
3. To what extent does AI adapt to the learning needs of students with different cognitive profiles, as measured by the Neethling Brain Instrument (NBI)?

In alignment with the Southern African Society for Engineering Education’s focus on student success, this study aims to inform the effective integration of AI with human-led instruction. The intensive five-day format compresses the learning cycle, potentially amplifying both the benefits and limitations of AI support, and may produce engagement and learning patterns that differ from those in longer interventions.

2 Methodology

2.1 Course Structure and Daily Schedule

This study was conducted at North-West University (NWU), South Africa, as part of a one-week intensive refresher course designed to reinforce key second-year engineering mathematics concepts before the semester commenced. The programme targeted common learning gaps to strengthen students' conceptual foundations for advanced coursework.

Forty-nine students from various undergraduate engineering programmes participated voluntarily, all enrolled in core second-year mathematics modules and with prior exposure to the topics.

The five-day course covered four foundational modules: MTHS 211 (Advanced Calculus), MTHS 212 (Linear Algebra), APPM 211 (Dynamics I), and APPM 212 (Differential Equations). Each day was dedicated to a single module, with Friday reserved for review and integration across all topics.

Students had access to the Mindjoy AI tutorbot throughout the day for independent practice and review. Each day included two instructor-led sessions (09:00–11:00 and 11:30–13:30) covering key concepts and guided problem-solving. In the late afternoon (16:30–18:30), all students participated in a compulsory AI-assisted session, during which they completed a short test on the day's content using Mindjoy. This session ensured consistent engagement with the platform while providing immediate, tailored feedback.

The week concluded with a Friday integration session focused on consolidating knowledge across modules, revisiting challenging material, exploring links between topics, and reflecting on learning in relation to students' cognitive profiles. This structure supported both conceptual understanding and self-directed learning through interactive AI support.

2.2 Data Collection Approach

A multi-source data collection strategy was used to analyse student engagement, learning behaviours, and the effectiveness of AI-assisted tutoring. Data came from three primary sources:

(1) AI-based engagement metrics

Interaction data were logged automatically by the Mindjoy platform throughout the week. Metrics included:

- Number of interactions (complete query–response pairs).
- Common misconceptions flagged by the system.

Misconceptions were identified from AI error logs and manually reviewed by instructors for accuracy and relevance. The tutor usage score was defined as the total number of discrete interactions per student during the refresher week, regardless of the number of modules attended or the total time spent on the platform.

(2) Student self-reported data

Neethling Brain Instrument (NBI) profiles were collected voluntarily from all participants, classifying cognitive preferences into four quadrants: L1 (analytical thinking), L2 (logical organisation), R1 (creative thinking), and R2 (social/holistic thinking). The NBI is a cognitive preference profiling tool rather than a traditional learning styles instrument; it identifies thinking preferences in four quadrants without making prescriptive claims about fixed learning modalities. It was selected for this study because it provides a quantifiable measure of thinking preferences that can be correlated with observed engagement patterns.

(3) Engagement constructs and perceptions

Google Form surveys captured:

- **Engagement constructs:**
  - Emotional Engagement (EE): motivation and enthusiasm when using AI.
  - Behavioural Engagement (BE): active participation in AI-assisted tasks.
  - Cognitive Engagement (CE): ability to connect AI-assisted learning to broader mathematical concepts.

- **Perceptions of the AI platform:** measured with the System Usability Scale (SUS) and a custom Perceived Learning (PL) questionnaire, both administered at the end of the week. Full item lists for these instruments are provided in Appendix A.

2.3 Data Analysis Approach

The data analysis aligned with the study's three research objectives:

- **Engagement:** The number of discrete conversations (query–response pairs) recorded for each participant during the refresher week was used as the measure of AI engagement.
- **Misconceptions:** The total number of misconceptions identified by the Mindjoy platform was recorded for each module.
- **Cognitive profiles:** NBI results were used to classify participants into four cognitive quadrants (L1, L2, R1, R2) and compared with tutor usage counts to explore patterns in AI interaction.
- **Engagement constructs and perceptions:** Survey responses were used to calculate Emotional Engagement (EE), Behavioural Engagement (BE), and Cognitive Engagement (CE) scores. The same survey included the System Usability Scale (SUS) and a custom Perceived Learning (PL) questionnaire, which were summarised to evaluate usability and perceived learning benefits.

All analyses were descriptive and conducted in Microsoft Excel.

3 Results

Quantitative survey results are presented separately from qualitative findings. Quotations are drawn from open-ended survey responses or informal verbal feedback. Numerical trends are based on survey ratings and platform analytics.

3.1 Tutorbot Usage and Student Engagement Trends

A key objective of this study was to examine how frequently students engaged with the AI tutor and how these usage patterns varied across the cohort.

3.1.1 Engagement Classification Criteria

Student engagement was categorised descriptively based on the total number of discrete AI tutor interactions (query–response pairs) recorded for each participant during the refresher week. Three usage categories were defined:

- High engagement: $\geqslant$ 38 interactions
- Medium engagement: 19–37 interactions
- Low engagement: $\leqslant$ 18 interactions

Descriptive statistics for each category are shown in Table 1. High-engagement students recorded between 44 and 83 interactions (median = 57.5), medium-engagement students between 20 and 36 (median = 28), and low-engagement students between 0 and 18 (median = 4).

The boxplot in Figure 1 illustrates these distributions, showing that high-engagement students consistently interacted more with the AI tutor, with a narrower spread at higher usage levels compared to the other groups.

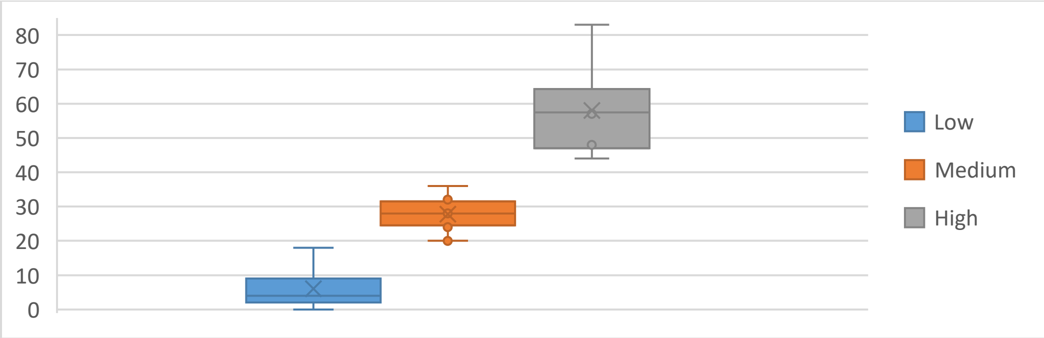

Figure 1: Tutorbot Usage vs. Engagement Level

3.2 Interpretation of Engagement Patterns

Highly engaged students (⩾ 38 interactions) frequently used the AI tutor for real-time problem-solving, feedback, and clarification, which indicates that they derived clear value from the structured, on-demand support it provided.

Medium-engagement students (19–37 interactions) tended to use the AI tutor selectively, often consulting it for specific problems rather than as a consistent study aid.

Low-engagement students (⩽ 18 interactions) showed minimal interaction with the AI tutor despite having full access throughout the week. In open-ended survey responses, these students reported barriers such as uncertainty about how to phrase questions, difficulty interpreting text-heavy responses, and a preference for face-to-face clarification.

Although daily tests were scheduled during the evening sessions, usage data indicate that students engaged with the AI tutor at various points during the day, including morning classes and independent study. Recorded usage therefore reflects a combination of scheduled and self-directed engagement.

Overall, these patterns reveal that AI tutors are most effective when students are already motivated and comfortable with text-based interaction. The variation in engagement levels highlights the potential benefit of expanding AI functionality to include more visual, collaborative, and adaptive features to better support different students' needs.

3.3 Misconceptions Across Modules and AI Effectiveness

Misconceptions were identified from AI tutorbot error logs generated during student interactions and manually reviewed by instructors to confirm accuracy and relevance to the course content. The highest number of misconceptions occurred in APPM 211 (20 cases), followed by APPM 212 (18) and MTHS 212 (15). MTHS 211 recorded 12 misconceptions, while 10 were general cross-module issues.

While Mindjoy analytics provided counts of misconceptions per module, these did not distinguish between procedural and conceptual types. The following two broad patterns are drawn from instructor observations and student comments, and are therefore qualitative rather than coded data categories.

Procedural misconceptions typically involved errors in applying known methods or executing calculation steps. Examples included:

- Numerical integration (APPM 211): Students applied Simpson's Rule without accounting for initial conditions, or confused it with unrelated numerical methods.
- Normal vector calculation (MTHS 212): Several students attempted to compute a normal vector from points without correctly using the vector product, or misread coefficients from a plane equation as the normal vector.

- Bernoulli's equation (APPM 212): Students omitted the substitution step needed to transform it into a linear equation, resulting in incorrect solutions.
- Row reduction (MTHS 212): Some students performed the basic operations but did not follow the logical sequence required for full reduction, leading to incorrect system solutions.

Conceptual misconceptions were linked to misunderstandings of underlying principles. Examples included:

- Rectilinear kinematics (APPM 211): Students struggled to relate position, velocity, and acceleration in continuous motion, often misapplying integration when deriving displacement.
- Geometric relationships between lines and planes (MTHS 212): Confusion over conditions for parallelism or skewness of lines/planes, and how vectors and planes interact geometrically.
- Exact differential equations (APPM 212): Misinterpreting the conditions for exactness, or confusing integrating factors with exact equations.
- Span and linear transformations (MTHS 212): Students conflated the meaning of "span" with generic combinations, or could not differentiate between definitions and applications of linear transformations.

These insights show that although the AI tutor was often effective in helping students correct procedural errors through step-by-step guidance, conceptual misunderstandings were more persistent, particularly when the explanations relied heavily on text. Addressing these would require incorporating interactive visual explanations, contextual hints, and follow-up questioning to encourage reflective thinking.

3.4 Cognitive Profiles and Tutorbot Engagement

This study examined how cognitive learning styles, as measured by the Neethling Brain Instrument (NBI), influenced engagement with AI tutoring. Students' dominant cognitive preferences were categorised into four quadrants: L1 (Analytical Thinking), L2 (Sequential Thinking), R1 (Creative Thinking), and R2 (Holistic/Relational Thinking).

Tutorbot usage was quantified as the total number of discrete AI–student interactions (complete query–response pairs) logged during the refresher week. Table 1 summarises the distribution of dominant NBI profiles across high, medium, and low engagement categories.

Table 1: Distribution of dominant NBI profiles across engagement categories

Engagement Category	**L1**	**L2**	**R1**	**R2**	**Total**
High (≥38)	4	2	0	0	6
Medium (19–37)	6	3	0	3	12
Low (≤18)	12	13	1	5	31
Total	22	18	1	8	49

Descriptive analysis showed that L1 (Analytical-Sequential) students recorded the highest median number of AI tutor interactions, followed by L2 (Organised-Practical) students, although L2 engagement varied more widely. R1 (Creative-Experimental) and R2 (Relational-Interpersonal) students tended to engage less frequently, and no R1 students appeared in the high-engagement group.

Figure 3 illustrates these patterns, showing that L1 students were more prevalent in the high- and medium-engagement categories, indicating that the AI tutorbot's structured, step-by-step explanations aligned closely with their preference for logical, sequential problem-solving. L2 students were present across all engagement levels but were most frequent in the low-engagement group, suggesting that while some adapted well to the AI format, others may have preferred more applied, hands-on approaches.

R1 students were absent from both high- and medium-engagement categories, with only a single low-engagement participant, indicating that the text-heavy format was less suited to their preference for exploratory, visually rich learning. R2 students appeared only in the medium- and low-engagement categories, consistent with a preference for collaborative, discussion-based learning over solitary AI interaction.

These findings highlight the need for AI tutors to integrate multimodal learning strategies (such as dynamic visualisations for R1 students, collaborative features for R2 students, and applied, context-based scenarios for L2 students) to ensure balanced engagement across diverse cognitive profiles.

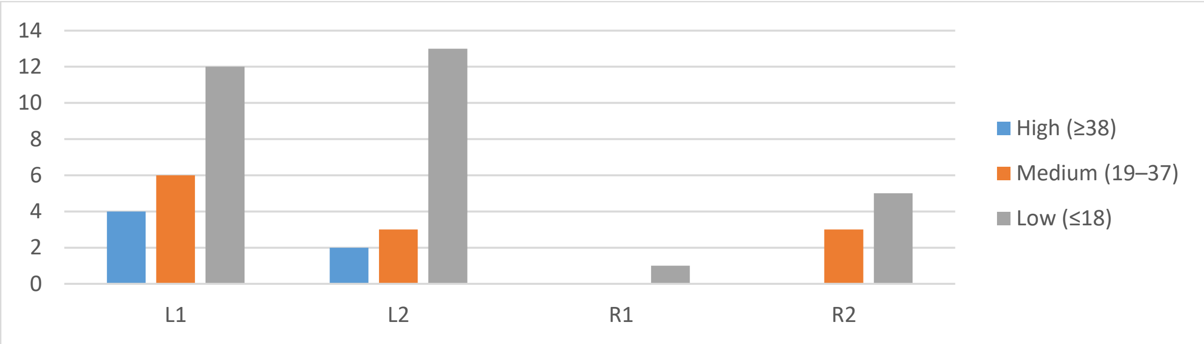

Figure 2: Engagement category vs. dominant NBI quadrant

3.5 Student Engagement Constructs and System Usability

Engagement constructs were measured using:

1. Survey-based self-reports (1–5 Likert-scale ratings capturing student perceptions of engagement),
2. Tutorbot usage analytics (total number of discrete student–AI interactions), and
3. Statistical summaries of survey ratings for Emotional Engagement (EE), Behavioural Engagement (BE), Cognitive Engagement (CE), System Usability (SUS), and Perceived Learning (PL).

Not all 49 students completed the survey items for these constructs; therefore, the results below are based only on respondents with complete data for each construct and a recorded NBI profile. Table 2 reports mean values (± standard deviation) for each construct by dominant cognitive profile.

Table 2: Mean Survey Ratings (Likert 1–5) for Engagement Constructs, System Usability, and Perceived Learning by Cognitive Profile

Dominant NBI Quadrant	Emotional Engagement (EE)	Behavioural Engagement (BE)	Cognitive Engagement (CE)	System Usability (SUS)	Perceived Learning (PL)
L1	3.45 ± 1.11	3.22 ± 1.15	3.92 ± 0.85	4.17 ± 0.84	3.89 ± 0.76
L2	3.60 ± 0.88	3.09 ± 1.15	4.20 ± 0.87	4.27 ± 0.92	4.10 ± 0.76
R2	3.90 ± 0.88	2.90 ± 0.99	2.60 ± 1.17	4.25 ± 0.64	4.00 ± 0.00

Note: Scores are based on 1–5 Likert ratings, reported as mean ± standard deviation.

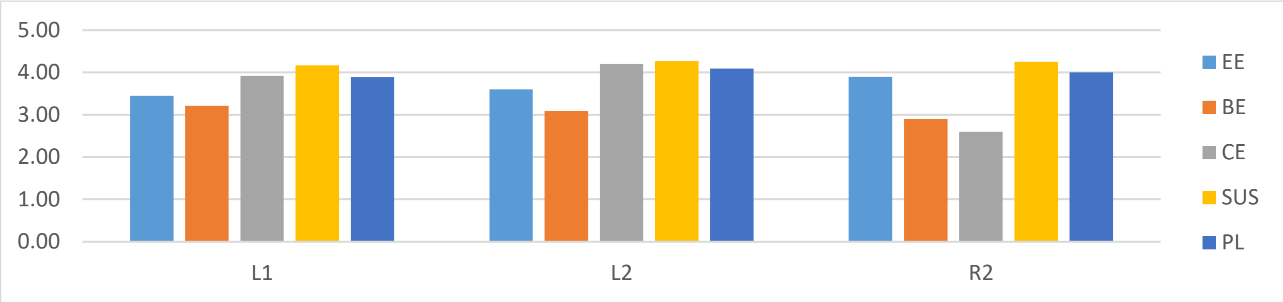

Figure 3: Mean ratings across the five constructs.

For emotional engagement (EE), R2 students reported the highest mean ratings (3.90), with L2 close behind (3.60), which implies that positive perceptions of the AI tutor were not limited to sequential thinkers. However, open-ended responses from R2 students indicated that these positive feelings did not always translate into sustained use, with some describing the AI as “impersonal” and preferring more collaborative interaction.

Behavioural engagement (BE) scores were moderate across all groups, with L1 slightly higher on average (3.22). This aligns with usage analytics showing that L1 students tended to complete more AI-assisted problem-solving sequences. R2 students recorded the lowest BE (2.90), often citing the “text-heavy interface” as discouraging for extended sessions.

In cognitive engagement (CE), L2 students reported the highest values (4.20), reflecting strong confidence in procedural problem-solving when using the AI tutor. L1 students followed closely (3.92), whereas R2 students had notably lower scores (2.60), consistent with their qualitative feedback that the AI “lacked conceptual depth” for complex reasoning tasks.

System usability (SUS) ratings were high for all profiles (4.17–4.27 range), indicating that students found the AI tutor generally easy to navigate and integrate into their learning routines. High SUS scores were moderately associated with higher usage, particularly among L1 and L2 students.

For perceived learning (PL), L2 students again led (4.10), followed by R2 (4.00) and L1 (3.89). Many L2 participants emphasised the value of step-by-step guidance for reinforcing key concepts, while R2 students stressed the need for more adaptive, context-rich explanations to support deeper understanding.

Overall, the data indicate that while the AI tutor was rated as usable and beneficial across cognitive profiles, its strengths were most evident for structured, sequential thinkers (L1 and L2). Creative and relational students (R2) engaged positively on an emotional level but showed lower behavioural and cognitive engagement, highlighting the importance of incorporating multimodal and collaborative features into AI-supported learning environments.

4 Discussions

As expected, students with a strong preference for structured, sequential learning (L1 profiles) engaged most readily with the AI tutorbot’s text-based, step-by-step feedback. The value of this study lies in quantifying the strength of that alignment and contrasting it with the markedly different engagement patterns of other cognitive profiles. By combining NBI profiling with detailed usage analytics and engagement constructs, we were able to pinpoint not only who engaged more, but also why, highlighting the specific features of the AI tutor that supported or limited each profile. These insights go beyond simply confirming known learning preferences, offering clear, evidence-based directions for improvement, such as incorporating multimodal elements to better support R1 and R2 students in engineering education contexts.

4.1 Tutorbot Effectiveness and Cognitive Profiles

This study examined the effectiveness of an AI-powered tutorbot in supporting engineering students' mathematics learning across different cognitive profiles (NBI). As shown in the results, L1 students (Structured Thinkers) recorded the highest engagement across all metrics, reflecting a strong alignment between their preference for clear, rule-based learning and the tutorbot's structured, step-by-step feedback. In contrast, R1 (Creative) and R2 (Social) students engaged less consistently, with several noting in open-ended responses that the AI felt "impersonal." This perception, coupled with the text-heavy interaction style, may account for their lower usage. Taken together, these findings point to the possibility that current AI tutor designs may inherently privilege structured students, highlighting the need for adaptive, multimodal interfaces that accommodate a wider range of cognitive styles.

4.2 Engagement Constructs in Context

Engagement with the AI tutor varied notably across cognitive profiles, underscoring the need to tailor digital learning tools to diverse student preferences. L1 students consistently reported high emotional, behavioural, and cognitive engagement, completing AI tasks more regularly and describing the system as both stimulating and effective for step-by-step problem-solving. This alignment reflects their preference for structured, rule-based environments and indicates that sequential students can thrive when AI-assisted contexts mirror their cognitive tendencies.

In contrast, R2 (Social) students reported mixed or lower engagement across some constructs. Many perceived the AI as impersonal or lacking emotional presence, leading to reduced behavioural engagement and difficulty sustaining focus. Cognitively, they often struggled to apply AI-generated feedback to real-world problems, particularly in the absence of collaborative or visual scaffolding.

The evidence shows that while structured AI systems effectively support L1 students, they risk marginalising students who rely on social interaction, exploratory learning, or visual reasoning. Addressing this gap requires moving beyond a one-size-fits-all approach toward adaptive, multimodal strategies that align more closely with diverse cognitive styles.

4.3 Implications for AI Tutor Design

The engagement disparities across cognitive profiles point to the need for AI tutors that are both flexible and adaptive. While structured students (L1) benefited from the linear, text-based format of the Mindjoy tutorbot, this approach was less effective for students who favour conceptual, collaborative, or visually driven learning. To engage a wider range of students, AI systems must evolve from static feedback toward responsive, multimodal interaction.

For R1 students, who thrive on visual pattern recognition and creative problem-solving, features such as interactive diagrams, animations, and graphing tools could enhance conceptual clarity. R2 students, who value interpersonal and language-based learning, may respond better to conversational scaffolding, discussion prompts, and simulated peer dialogue. In both cases, adaptive branching logic (adjusting tone, strategy, or pacing based on user profile) could substantially improve engagement and learning outcomes.

Personalisation in AI learning should go beyond adjusting content level or delivery speed. Considering how students think and interact with information can shift AI tutors from rigid information providers to responsive, context-aware learning partners.

4.4 AI Usability and Learning Outcomes

The System Usability Scale (SUS) and Perceived Learning (PL) results offer valuable insights into how students experienced the AI tutorbot. Most participants rated the system as intuitive and easy to navigate, with a mean SUS score of 4.21. This aligns with prior research showing consistently high usability ratings for AI-based learning tools, particularly when they provide structured, step-by-step interaction (Vlachogianni & Tselios, 2021; Wang et al., 2024). Students also reported that the tutorbot enhanced their learning, especially in consolidating procedures and supporting independent problem-solving.

However, these positive perceptions were not evenly distributed across cognitive styles. L1 students rated both usability and learning impact highly, whereas R2 students struggled with dense, text-heavy explanations and often disengaged due to limited interactivity or conceptual scaffolding. This indicates that strong usability in technical terms does not necessarily translate into high cognitive or emotional engagement for all students.

For broader adoption and greater impact, future AI systems should pair usability with adaptive learning features (such as progressive onboarding, multimodal feedback, and differentiated interaction modes) to better serve students who think and engage in different ways. High usability should be treated as a necessary starting point, not the ultimate measure of an inclusive AI learning tool.

4.5 Limitations

While this study offers valuable insights into AI-assisted mathematics learning, several limitations must be considered. First, the implementation was confined to the Mindjoy tutorbot within a structured refresher and intervention setting, meaning the results may not generalise to other AI systems or contexts without comparable scaffolding and instructor support.

Second, as noted in the Results section on Misconceptions Across Modules, the AI tutor displayed limited conceptual flexibility. Although effective in guiding students through procedural steps, it often struggled to address deeper conceptual misunderstandings or adapt explanations dynamically, particularly among students with R1 and R2 learning profiles.

Third, as highlighted in the Student Engagement Constructs and System Usability results, the absence of visual and interactive elements reduced engagement for some students, especially those with visual or kinaesthetic preferences. The lack of diagrams, simulations, or collaborative tools underscores the importance of multimodal support in future AI designs.

Fourth, certain students (particularly those less familiar with AI) experienced cognitive overload when presented with long, text-heavy feedback. Progressive scaffolding, beginning with simplified explanations and gradually increasing complexity, could mitigate this challenge.

Finally, the study’s modest sample size (n = 49) and homogeneous participant profile (engineering undergraduates at a single institution) limit the generalisability of results. Future research should include a more diverse student base across disciplines and institutions, and employ longitudinal designs to assess the sustained impact of AI tutors on conceptual understanding and academic performance.

5 Conclusion

This study examined how engineering students with different cognitive profiles engaged with an AI tutorbot during an intensive mathematics refresher course. By combining NBI profiling with survey-based engagement constructs, usage analytics, and perceived learning measures, the analysis addressed three research questions.

First, student engagement varied markedly across cognitive profiles: L1 students recorded the highest levels of interaction, followed by L2 students, while R1 and R2 students engaged far less, no R1 students appeared in the high-engagement category.

Second, AI support proved more effective in addressing procedural misconceptions than conceptual ones. Step-by-step guidance often corrected calculation errors, but deeper conceptual misunderstandings persisted, particularly when explanations relied solely on text.

Third, the AI tutor displayed limited adaptability to diverse cognitive needs. Its structured, text-based format aligned well with sequential thinkers (L1), but creative (R1) and relational (R2) learners called for more visual, interactive, and discussion-oriented features.

These findings quantify the alignment between AI affordances and student preferences while offering targeted design directions (such as incorporating multimodal content, adaptive feedback, and collaborative features) to extend benefits across a broader range of learners. Advancing beyond confirmation of known learning tendencies, this work provides evidence-based recommendations for more inclusive, adaptive AI tutor design in engineering mathematics education.

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APPENDIX A – EE, BE, CE, SUS and PL Structured Questions

Emotional Engagement (EE)

(1) I feel excited when solving math problems with the AI tool.
(2) I enjoy learning math concepts using AI-based tools.
(3) I feel emotionally involved when solving problems with the AI tool.
(4) The use of AI tools makes learning enjoyable for me.
(5) I feel curious about what we are learning when using the Tutorbot.

Behavioural Engagement (BE)

(1) I try hard to engage actively with the AI tool during lessons.
(2) I complete all tasks provided through the AI tool.
(3) I participate fully in discussions or exercises involving AI-based tools.
(4) I actively explore how to use the AI tool to enhance my problem-solving.
(5) I work hard when engaging with the Tutorbot.

Cognitive Engagement (CE)

(1) I try to connect concepts I learn with the AI tool to my prior knowledge.
(2) I use the AI tool to help integrate various mathematical ideas.
(3) I reflect on how the AI tool supports my problem-solving skills.
(4) I apply critical thinking when interacting with the AI tool.
(5) I evaluate the effectiveness of the AI tool in helping me understand complex concepts.

System Usability Scale (SUS)

(1) I think that I would like to use the Tutorbot frequently.
(2) I found the Tutorbot to be simple.
(3) I thought the Tutorbot was easy to use.
(4) I think that I could use the Tutorbot without the support of a technical person.
(5) I found the various functions in the Tutorbot to be well integrated.
(6) I thought there was a lot of consistency in the Tutorbot.
(7) I would imagine that most people would learn to use the Tutorbot very quickly.
(8) I found the Tutorbot to be very intuitive.
(9) I felt very confident using the Tutorbot.
(10) I could use the Tutorbot without having to learn anything new.

Perceived Learning (PL)

(1) The Tutorbot provided me with an integrated knowledge of the mathematical concepts covered in the refresher course.
(2) The Tutorbot enhanced my ability to investigate, discuss, and critique mathematical problems more effectively.
(3) The Tutorbot enhanced my ability to apply mathematical techniques to solve problems.
(4) The Tutorbot helped me to develop a deeper understanding of mathematical principles and their applications.
(5) The Tutorbot improved my ability to analyse and solve complex mathematical problems.
(6) The Tutorbot developed my ability to apply problem-solving strategies in mathematics.

Open-Ended Questions

(1) How has the use of AI tools impacted your learning experience?
(2) What do you find most helpful about the AI tool?
(3) Are there any challenges you encountered while using the AI tool? Please elaborate.
(4) What suggestions do you have for improving the AI tool or its integration into learning?