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ORIGINAL ARTICLE

Foundation Students' Engagement with AI Math Tools on Awareness, Usage Purposes and Perceptions

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ABSTRACT - This study examines foundation-level students' engagement with AI-based math tools by investigating their awareness, academic usage purposes, and perceptions. A quantitative, cross-sectional survey design was adopted, involving 340 students from the School of Foundation Studies at the University of Technology Sarawak. Participants completed an online questionnaire covering three domains: initial discovery of AI math tools, academic usage purposes, and perceptions across four constructs: Perceived Usefulness, Learning Impact, Trust and Value, and Behavioural Intention to Use. Descriptive analysis revealed that students most commonly became aware of AI tools through peer recommendations, social media, and educational institutions. In terms of academic usage, AI tools were primarily used for solving problems, checking homework, and understanding new concepts, with less frequent use for graphing, exploring theories, and complex calculations.
Perception analysis showed that students generally viewed AI tools positively. Based on a four-point Likert scale (1 = Strongly Disagree, 4 = Strongly Agree), Perceived Usefulness (M = 2.99) and Learning Impact (M = 2.97) recorded the highest mean scores, followed by Trust and Value (M = 2.87). Behavioural Intention to Use was comparatively lower (M = 2.65), indicating some hesitation about continued use. This may be due to uncertainty about tool reliability, limited awareness of advanced functions, or concerns about overdependence. The findings highlight the influential role of informal discovery channels and the task-oriented nature of current AI tool usage. In addition, the results emphasize the need for structured institutional efforts to promote ethical, informed, and deeper integration of AI tools in mathematics education, supporting long-term engagement and improved learning outcomes.

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INTRODUCTION

The integration of artificial intelligence (AI) into education has significantly transformed how students engage with mathematics. Tools such as ChatGPT, Photomath, and Microsoft Math Solver now offer functionalities like equation solving, graph visualization, and step-by-step guidance, serving as interactive supports alongside traditional instruction. These AI-driven applications assist learners in tackling complex mathematical topics such as derivatives, integrals, and rates of change, while providing immediate, individualized assistance [1-2].

More broadly, AI is becoming increasingly embedded in digital learning environments across disciplines, particularly through intelligent tutoring systems (ITS) and adaptive assessment platforms. In mathematics education, these tools are not only used to solve problems but also to verify solutions,

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explore alternative strategies, and deepen conceptual understanding. Their accessibility on mobile and web platforms makes them especially appealing to students who prefer autonomous and flexible learning. For those who struggle with foundational concepts, AI tools offer scaffolding that promotes self-directed learning and builds academic confidence. Recent studies show that mobile learning environments, many of which incorporate AI components, have a positive effect on students' mathematics achievement by supporting deeper understanding through interactive features and engaging instructional design [3-4].

AI has seen rapid adoption in mathematics education, particularly at the secondary and higher education levels. Studies demonstrate that AI tools provide personalized learning experiences, adaptive tutoring, and enhanced engagement in both school and university mathematics contexts. For example, [5] examined the role of AI tools such as ChatGPT in mathematics teaching across secondary schools and higher education, highlighting their potential to transform learning environments. At the undergraduate level, AI-based platforms have been implemented to support engineering students in learning mathematics, with positive feedback on user experience and learning outcomes [6]. Similarly, [7] explored AI applications in higher education mathematics teaching, identifying opportunities for improved personalization and efficiency. Systematic reviews further confirm that AI research in mathematics education is concentrated at the secondary and undergraduate levels, with tools like intelligent tutoring systems and ChatGPT widely studied [8-9]. In contrast, limited research has focused on foundation-level or preparatory students who are still developing essential mathematical competencies. Existing studies at this stage primarily emphasize broader pedagogical strategies, such as project-based learning, without explicitly employing AI tools [10]. This imbalance demonstrates that although AI tools are increasingly studied in mathematics education, their application to foundation-level learners remains scarce.

Engagement at the foundation level is pedagogically important because this phase lays the groundwork for students' confidence, motivation, and transition into higher-order mathematical reasoning. Evidence from studies involving foundation-programme mathematics students shows that engagement-oriented learning experiences contribute to higher levels of motivation and improved mathematical performance, indicating that engagement at this stage plays a meaningful role in preparing students for subsequent coursework [11]. This is consistent with broader findings in mathematics education showing that students who are more engaged tend to demonstrate stronger motivation, confidence, and achievement, supporting deeper reasoning and more meaningful participation in learning [12].

If foundation-level students continue to receive limited research attention, a potential challenge is that important differences in how they access and use AI-based mathematics tools may not be well understood. This can reduce the relevance of technology-enhanced learning approaches, as existing evidence is largely based on broader higher-education contexts rather than on the specific learning characteristics of foundation-level students [13].

The extent to which these students are aware of AI math tools, the purposes for which they use them, and how they evaluate their benefits remains underexplored. To address this gap, the present study investigates foundation students' engagement with AI-based math tools across three key dimensions: awareness, academic usage purposes, and perceptions, specifically focusing on perceived usefulness, learning impact, trust and value, and behavioural intention to use. Understanding how students discover, utilize, and evaluate these tools can inform more strategic and equitable integration of AI in mathematics education. The findings aim to support educators and institutions in designing AI-informed instructional practices that enhance both learning outcomes and student agency.

Research Objectives

This study investigates how foundation-level students engage with AI-based math tools, focusing on the following objectives:

1. To explore the initial channels through which students become aware of AI math tools.
2. To identify the various academic purposes for which students use AI math tools.
3. To examine students' perceptions regarding the perceived usefulness, learning impact, trust and value, and behavioral intentions associated with these tools.

Research Questions

RQ1: How do students first become aware of AI math tools?
RQ2: For what purposes do students use AI math tools in their academic learning?
RQ3: What are students' perceptions of AI math tools in terms of perceived usefulness, learning impact, trust and value, and behavioral intention?

LITERATURE REVIEW

Integration of AI in Mathematics Education

The integration of AI into mathematics education is reshaping traditional teaching and learning practices, offering numerous benefits while also presenting certain challenges. AI-driven tools such as ChatGPT and ITSs provide personalized learning experiences by adapting to individual student needs and delivering targeted feedback [2; 9; 14]. These technologies enhance student engagement and motivation by fostering dynamic and interactive learning environments [2]. Additionally, AI facilities real-time assessment and feedback, allowing students to gain immediate insights into their performance and areas for improvement [9; 15-16].

Tools such as MathGPT and Wolfram Alpha assist in understanding complex mathematical concepts and refining problem-solving skills through continuous interaction and well-designed prompts [2]. These tools enhance conceptual understanding by supporting the visualization of mathematical problems and providing step-by-step solutions [2; 8].

Awareness and Adoption Channels of AI Tools

The level of awareness and adoption of AI tools in educational contexts is influenced by multiple factors and exposure channels. Students and educators are more likely to adopt AI technologies when they perceive them as both useful and easy to use [17-20]. These perceptions have a strong influence on behavioral intentions and actual tool usage. Social influence, particularly from peers and institutional environments, plays a crucial role in encouraging adoption [19; 21-22]. Positive attitudes from peers and institutional infrastructure further enhance students' willingness to integrate AI tools into their academic practices.

Educational institutions, particularly universities and schools, act as key facilitators by incorporating AI tools into curriculum and providing necessary technical support [22-24]. In addition, online sources such as websites, academic publications, and user forums are critical in spreading awareness by providing accessible information and practical tutorials [25]. Community networks and peer recommendations also play an important role. Positive experiences often encourage further adoption, as users share success stories and tool benefits [19; 21].

Academic Use of AI Math Tools

AI mathematics tools are widely used for generating examples, solving problems, evaluating difficulty, Students utilize AI math tools for a wide range of academic tasks, including generating worked examples, solving problems, assessing problem difficulty, and preparing for examinations [1]. Tools such as ChatGPT and Photomath are frequently used as cognitive supports during problem-solving, particularly in exploratory contexts. These applications help break down complex tasks into manageable steps, reducing anxiety related to mathematical challenges [26].

One of the main benefits of these tools is their support for iterative reasoning. Rather than providing final answers alone, AI tools encourage users to refine their inputs and reasoning through trial-and-error processes. [27] found that such interaction enhances understanding of both accurate and flawed problem-solving strategies. Similarly, [28] observed that students often compare their thinking with AI-generated solutions, which promotes reflective thinking and metacognitive development.

Students' Perception towards AI Math Tools

Students generally express positive perceptions of AI math tools, acknowledging both their benefits and the challenges they may present. When supported with proper training and ethical guidance, these tools are more likely to be accepted and used effectively in educational environments. Many students report practical experience with AI tools and express a sense of comfort and familiarity in their usage [29].

AI tools are widely perceived as useful for improving learning outcomes through personalized instruction, adaptive feedback, and support in developing effective problem-solving strategies [30-31]. Research further indicates that such tools contribute to measurable gains in students' mathematical performance and analytical reasoning [31]. Applications like ChatGPT are viewed as engaging and motivational, providing instant academic assistance across a variety of tasks [1; 32]

Trust levels in generative AI chatbots vary between student groups. Among low-performing students, trust levels tend to change significantly over time, while those of high performers remain relatively stable. Despite these patterns, trust in AI tools does not necessarily correlate with computational thinking, self-regulated learning, or overall academic performance. However, trust can still influence students' expectations and their behavioural intention to use these tools [33].

Perceived usefulness and enjoyment have both been identified as significant factors influencing students' evaluation of AI tools, particularly in terms of ease of use, overall value, and their intention to continue using them [34].

THEORETICAL AND CONCEPTUAL FRAMEWORK

Theoretical Perspectives Informing the Study

Research on students' engagement with digital and AI-based learning tools has been grounded in several theoretical perspectives. Prior studies have commonly applied the Technology Acceptance Model (TAM) to explain how learners' perceptions of usefulness and ease of use shape their intention to use educational technologies [35]. Other related frameworks include the Unified Theory of Acceptance and Use of Technology (UTAUT), which emphasises the roles of performance expectancy, effort expectancy, social influence, and facilitating conditions in technology engagement [36]; the Theory of Planned Behaviour (TPB), which links behavioural intention to attitudes, subjective norms, and perceived behavioural control [37]; and Expectation–Confirmation Theory (ECT), which is often used to explain students' continued use of learning technologies based on satisfaction and performance expectations [38]. In the learning and motivation domain, frameworks such as Self-Determination Theory (SDT) have also been applied to explain student engagement through constructs such as autonomy, competence, and intrinsic motivation [39].

Rationale for Adapting TAM as the Primary Lens

In this study, the TAM framework is adapted as the guiding theoretical lens because it has been widely applied and validated in educational technology research, and its core structure provides a flexible basis for examining students' perceptions and behavioural intention in different learning contexts. Recent empirical research in educational contexts has applied TAM to explain students' acceptance and engagement with digital learning technologies. For example, TAM has been used to examine students' acceptance of online self-learning environments [40], extended examinations of blended and e-learning adoption [41], and comprehensive reviews of technology acceptance in mobile learning contexts [42], as well as in the adoption of learning management systems in Education 4.0 teaching and learning environments [43]. These studies collectively demonstrate the continued relevance of TAM in explaining perceived usefulness, perceived ease of use, and behavioural intention within contemporary educational technology research.

Adapted TAM Constructs in This Study

Building on TAM, the present study retains Perceived Usefulness and Behavioural Intention to Use as core acceptance constructs, while incorporating Learning Impact and Trust and Value as context-specific extensions that reflect students perceived learning benefits and confidence in AI-based mathematics tools. These constructs are particularly relevant for foundation-level learners, who may rely on such tools not only for usability, but also for their contribution to understanding, trust in output quality, and perceived academic value. Within the TAM perspective, students' interaction with learning technologies is explained through their behavioural intention to use the tools, which is shaped by their cognitive and value-related perceptions of the system [44]. In this study, behavioural intention to use is therefore interpreted as an indicator of student engagement with AI-based mathematics tools. Consistent with TAM findings in educational contexts, students continued use of learning technologies is largely shaped by their perceptions of usefulness and the learning value they attribute to the technology, and in this study, these perceptions are applied to AI-based mathematics tools [42; 45]. In the foundation-level context of this study, these perceptions are reflected in the constructs of perceived usefulness, behavioural intention to use, learning impact, and trust and value, which together shape students' reliance on AI-based mathematics tools and act as key drivers of engagement.

To clarify how these constructs relate to the original TAM structure, Table 1 presents a mapping between the original TAM constructs and the constructs used in this study.

Table 1. Mapping of Original TAM Constructs to the Constructs Used in This Study

No.	Original TAM Construct	Corresponding Construct in This Study	Status / Interpretation
1	Perceived Usefulness (PU)	Perceived Usefulness (PU)	Equivalent construct (retained)
2	Perceived Ease of Use (PEOU)	Not measured in the final model	Not retained at item level during instrument validation (weak factor loading)
3	Attitude Toward Using (ATT)	Not measured in this study	Not included in the adapted model
4	Behavioural Intention to Use (BI)	Behavioural Intention to Use (BI)	Equivalent construct (retained)
5	Actual System Use (AU)	Not measured in this study	Not included in the adapted model
6	-	Learning Impact (LI)	Extension construct (retained)
7	-	Trust and Value (TV)	Extension construct (retained)
8	-	Satisfaction	Extension construct (not retained due to low factor loading during instrument validation)

The table shows that the adapted model retains the core TAM constructs of Perceived Usefulness and Behavioural Intention to Use, while Learning Impact and Trust and Value are incorporated as extension constructs relevant to AI-supported mathematics learning. These extensions are consistent with prior research showing that, in educational technology contexts, students' engagement with digital tools is shaped not only by usefulness perceptions, but also by perceived learning benefits and evaluations of the added academic value of technology-mediated learning support [42-43]. By contrast, Perceived Ease of Use and Satisfaction were not retained in the final empirical model, as their indicators demonstrated weak psychometric performance and were therefore excluded at the item level during instrument validation, consistent with recommendations in the validation literature, where weakly loading indicators are removed to improve construct validity and reliability [46-48]. Attitude toward Using and Actual System Use were not included in the adapted model because they were not measured in this study.

This approach aligns with prior extensions of TAM in which original constructs have been omitted when their contribution was weak or redundant. For example, in TAM2, Attitude toward Using was completely removed from the model [44]. In other studies, Perceived Ease of Use has been found to play a comparatively weaker empirical role in learning contexts, even when retained in the model [45], and TAM constructs are frequently adapted to suit contextual requirements [49]. The corresponding measurement-model results are reported in the Instrument Validation section. For clarity, Figure 1 presents a visual representation of the adapted TAM framework, showing the original and extension constructs that were retained and those that were not retained following instrument validation in this study.

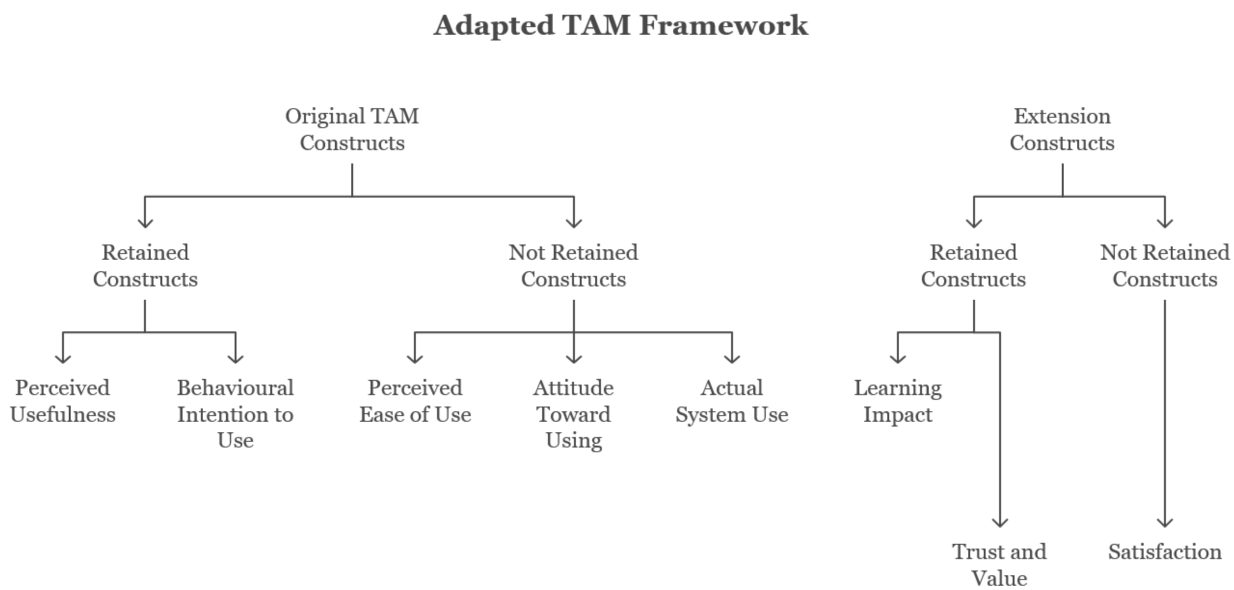

Figure 1. Adapted TAM framework showing the retained and not retained original and extension constructs following instrument validation.

METHODOLOGY

Research Design

This study adopted a quantitative, cross-sectional survey design to examine foundation students' engagement with AI-based math tools. This design allowed for the collection of data at a single point in time, capturing how students discovered these tools, how they use them academically, and their perceptions of their effectiveness and trustworthiness. The approach enabled the identification of usage patterns and attitudinal trends within a defined student population.

Study Context and Participants

The research was conducted at the University of Technology Sarawak (UTS) and focused on students enrolled in the School of Foundation Studies (SFS). Participants were drawn from the two programmes offered, Foundation in Arts (FIA) and Foundation in Science (FIS). A simple random sampling technique was employed, using the full foundation cohort as the sampling frame. A total of 340 students were randomly selected to complete an online survey administered via Google Forms. Participation was voluntary and anonymous to encourage honest and unbiased responses.

Instrumentation

A structured questionnaire was designed to assess students' engagement with AI math tools across three domains: discovery of tools, purpose of use, and perceptions concerning perceived usefulness, learning impact, trust and value, and behavioral intention to use. The first section featured a multiple-choice question on how students initially discovered AI math tools, with options including: online ads, peer or family recommendations, school introductions, social media, reviews or articles, search engines, and an open "Other" field.

The second section asked about the purposes of use, again using a multiple-choice format. Options included solving problems, visualizing graphs, understanding new concepts, checking homework, performing complex calculations, exploring mathematical theories, and "Other."

The third section comprised 20 statements measured on a 4-point Likert scale (1 = Strongly Disagree to 4 = Strongly Agree). These items were developed based on an adapted TAM framework, in which two original TAM constructs (Perceived Usefulness and Behavioral Intention to Use) were retained, and two context-specific constructs (Learning Impact and Trust and Value) were incorporated for the AI mathematics context. The wording of several items was informed by a related study examining students' experiences with ChatGPT in a mathematics learning context [50], but all statements were newly written or contextually modified for this study.

Instrumentation Validation

To ensure that the questionnaire effectively captured students' perceptions of AI math tools, the 20 Likert-scale items were aligned with four constructs used in this study: Perceived Usefulness, Learning Impact, Trust and Value, and Behavioral Intention to Use. Two of these constructs were retained from the TAM framework (Perceived Usefulness and Behavioral Intention to Use), while Learning Impact and Trust and Value were introduced as context-specific extensions to suit the foundation-level mathematics learning context. Each statement was mapped to one of the four constructs to establish conceptual clarity and content validity. Specifically, statements 2, 3, 4, 12, 13, and 14 represented Perceived Usefulness; statements 5, 8, 9, 10, and 11 corresponded to Learning Impact; statements 6, 7, 16, and 18 were aligned with Trust and Value; and statements 15, 17, and 20 measured Behavioral Intention to Use.

During the initial analysis, two items, Statement 1 and Statement 19, demonstrated low standardized loadings of only 0.224, indicating weak associations with their intended constructs. Consequently, these items were excluded from the measurement model to enhance construct validity and strengthen the overall reliability of the scale. To enhance clarity regarding construct alignment and item development, Table 2 presents the full list of questionnaire items grouped by construct, including the two items that were later excluded during instrument validation.

Table 2. Questionnaire Items Grouped by Construct

Construct	Statement No.	Item Description	Remark
Perceived Usefulness	Statement 2	AI math tools have helped me learn and reinforce various mathematical concepts.	Retained
	Statement 3	AI math tools have enabled me to solve problems in mathematics.	
	Statement 4	AI math tools have helped me complete scheduled tasks and assignments outside the classroom.	
	Statement 12	AI math tools are more effective than traditional methods (e.g., notes, textbooks) in supporting my mathematics learning.	

	Statement 13	AI math tools sufficiently meet my needs for assignments, requiring no additional resources.	
	Statement 14	Integrating AI mathematical tools into the classroom environment is highly beneficial.	
Learning Impact	Statement 5	Using AI math tools has significantly improved my confidence and ability to solve mathematics problems.	Retained
	Statement 8	AI math tools have positively impacted my learning and understanding of mathematics.	
	Statement 9	AI math tools can greatly improve the development of problem-solving skills.	
	Statement 10	AI math tools have a positive impact on enhancing critical thinking skills.	
	Statement 11	AI math tools can lead to better outcomes in group work.	
Trust and Value	Statement 6	The answers generated by AI math tools are consistent with theoretical mathematical concepts.	Retained
	Statement 7	The solutions from AI math tools are accurate when it comes to numerical calculations.	
	Statement 16	I am confident in the privacy and ethical standards of using AI math tools.	
	Statement 18	I believe AI math tools are important resources in academia.	
Behavioural Intention to Use	Statement 15	I rely on AI tools to study mathematics.	Retained
	Statement 17	I am willing to purchase the premium version if necessary for AI math tools.	
	Statement 20	I will definitely recommend using AI math tools to others.	
Excluded Items	Statement 1	It is easy to use AI math tools for solving my mathematical problems.	Originally Perceived Ease of Use
	Statement 19	My experience using AI math tools is satisfactory.	Originally Satisfaction

Note. Items listed under "Excluded Items" were excluded during instrument validation due to low factor loadings (≈ .224).

Following the item mapping and refinement process, the structure and reliability of the measurement instrument were evaluated using two statistical procedures. First, Confirmatory Factor Analysis (CFA) was performed to assess the fit of the proposed four-factor model. The user model yielded a chi-square value of 396 (df = 129, $p < .001$), indicating an acceptable model fit. The Standardized Root Mean Square Residual (SRMR) was 0.054, and the Root Mean Square Error of Approximation (RMSEA) was 0.078 with a 90% confidence interval of 0.069 to 0.087. Additional indices further supported the model's robustness: the Comparative Fit Index (CFI = 0.995), Tucker-Lewis Index (TLI = 0.994), Normed Fit

Index (NFI = 0.992), and Incremental Fit Index (IFI = 0.995) all exceeded the recommended 0.90 threshold. While the Parsimony Normed Fit Index (PNFI) was slightly lower at 0.836, this is common for parsimony-adjusted indices and does not detract from the overall model quality.

The standardized factor loadings provided further evidence of construct validity. Perceived Usefulness items ranged from 0.727 to 0.855, Learning Impact items from 0.839 to 0.882, Trust and Value items from 0.692 to 0.858, and Behavioral Intention to Use items from 0.651 to 0.807. These results confirmed strong item-construct associations and satisfactory convergent validity.

Second, Cronbach's Alpha was calculated for construct to access the internal consistency. The reliability results indicate good internal consistency for Perceived Usefulness (α = 0.850), Learning Impact (α = 0.884), and Trust and Value (α = 0.788), all of which fall within the good-to-acceptable range. Although the alpha value for Behavioral Intention to Use was slightly lower (α = 0.677), values above 0.60 are generally considered acceptable in exploratory research and were supported by adequate factor loadings. Cronbach's alpha thresholds followed the guideline that values $\geq$ 0.70 are acceptable and values $\geq$ 0.60 are acceptable in exploratory research [51, 52]. Overall, these results confirm that the measurement instrument was both conceptually sound and statistically reliable for evaluating students' perceptions of AI math tools.

Data Analysis Method

Data analysis was conducted according to the study's three research objectives. For the first and second objectives, which explored how students become aware of AI math tools and the purposes for their use, descriptive statistics were applied. Frequencies were calculated to summarize the number of responses for each option, as both survey items allowed multiple selections. Each selected response was treated independently in order to identify the most common sources of awareness and the primary academic uses of AI math tools.

To address the third objective, which focused on students' perceptions, the 18 Likert-scale items were grouped into four validated constructs: Perceived Usefulness, Learning Impact, Trust and Value, and Behavioral Intention to Use. Composite scores were computed by averaging the item responses within each construct. The mean and standard deviation were then calculated to summarize the central tendency and variability of students' responses across each construct.

All statistical analyses were performed using Jamovi (Version 2.6.44), an open-source statistical software platform developed to support transparent and reproducible data analysis in the social sciences.

RESULTS AND DISCUSSION

Students' Initial Awareness of AI Math Tools

This section presents the results for RO1, which aimed to explore how foundation students first became aware of AI math tools. As respondents were allowed to select multiple sources, the results reflect the frequency of each awareness channel and these frequencies are illustrated in Figure 2.

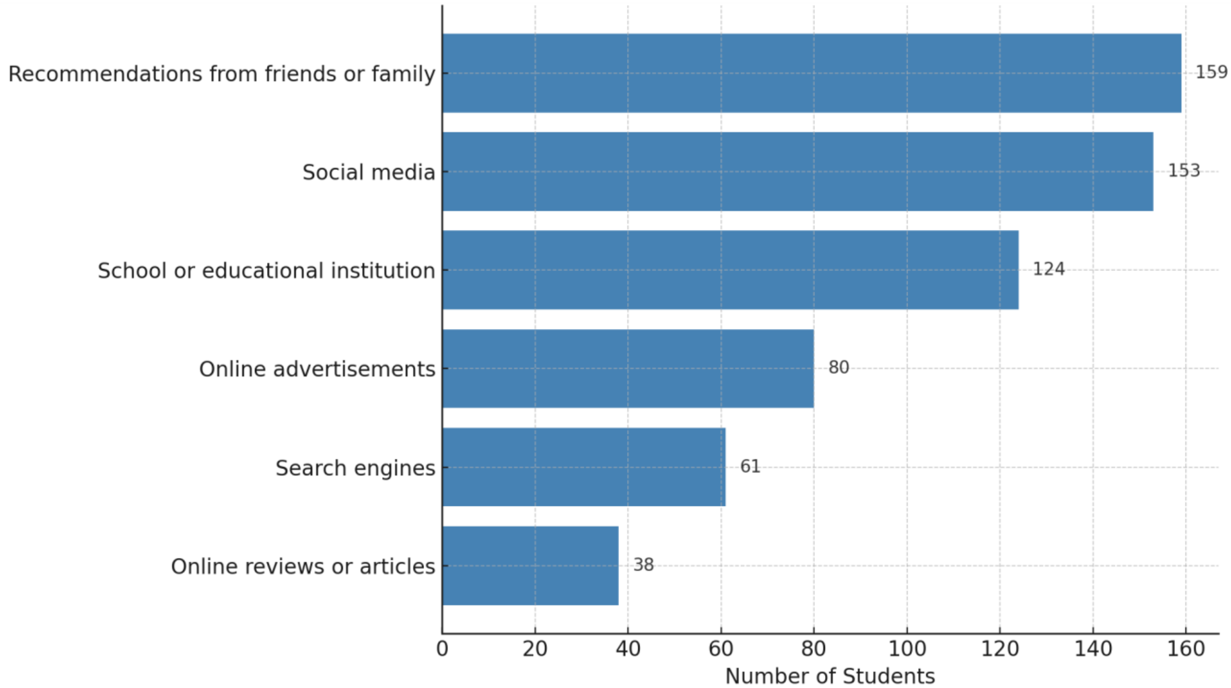

Figure 2. Frequency of Awareness Channels for AI Math Tools

The findings reveal that the most commonly reported source of awareness was recommendations from friends or family, selected by 159 students. This was followed closely by social media (153 students) and school or educational institutions (124 students). Less frequently reported channels included online advertisements (80), search engines (61), and online reviews or articles (38). Notably, none of the students selected the "Other" option, suggesting that the predefined response categories sufficiently captured the full range of relevant sources.

These results indicate that students primarily became aware of AI math tools through informal, peer-driven, and digital platforms rather than through structured institutional efforts. The prominence of friends, family, and social media reflects the influence of social networks and online ecosystems in shaping students' exposure to emerging technologies. While educational institutions did contribute to awareness, they ranked third, suggesting that formal promotion or integration of AI tools in curriculum settings may be limited or inconsistent.

This pattern aligns with broader trends in student technology adoption, where the discovery and initial use of digital tools are often self-initiated or community-driven rather than formally guided [53, 54, 55]. The findings suggest an opportunity for educational institutions to play a more proactive role in curating and endorsing high-quality AI tools for learning. Given the increasing role of AI in education, universities and schools could consider embedding such tools into orientation programs, study skills workshops, or course-specific resources, not only to increase visibility but also to promote informed and ethical use.

Students' Academic Purposes for Using AI Math Tools

This section addresses RO2, which explored the academic purposes for which students use AI-based math tools. As in the previous item, students were allowed to select multiple options. The distribution of responses is shown in Figure 3 and reflects the diverse ways these tools are applied in mathematical learning.

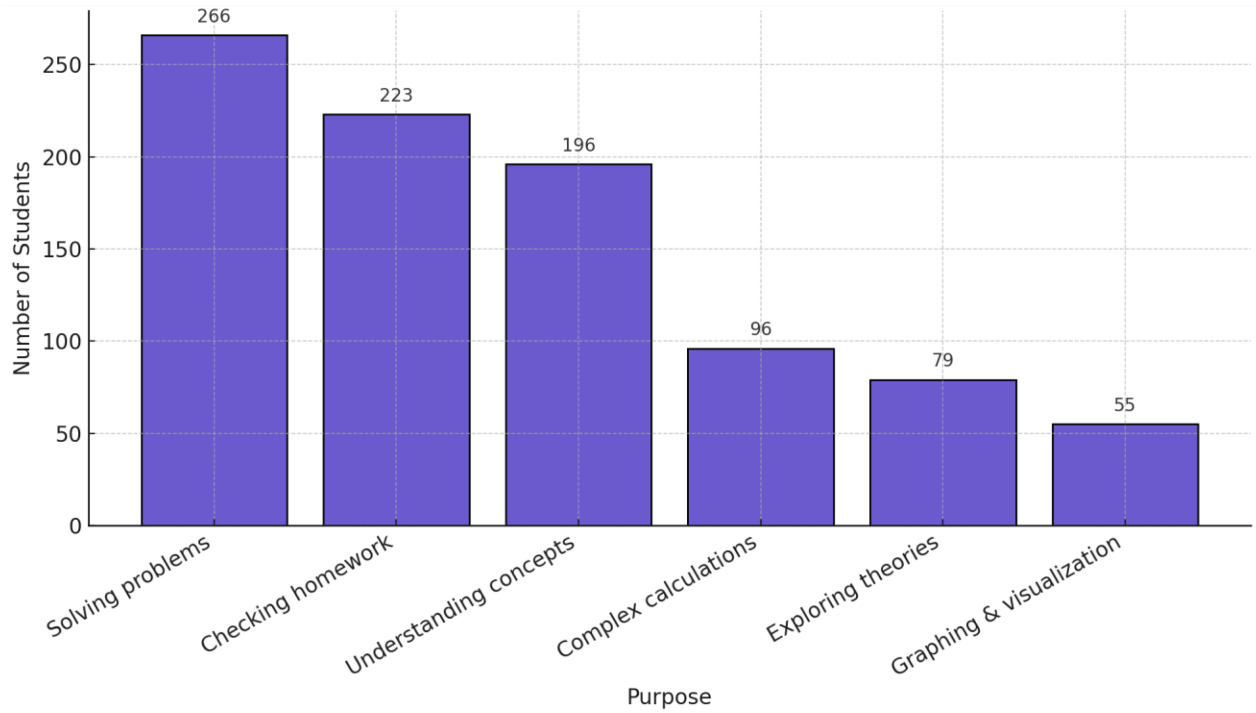

Figure 3. Frequency of Academic Purposes for Using AI Math Tools

The most commonly reported purpose was solving mathematical problems, selected by 266 students. This was followed by checking homework or assignments (223 students) and understanding and learning new concepts (196 students). Less frequent responses included performing complex calculations (96 students), exploring mathematical theories and proofs (79 students), and drawing graphs or visualizing functions (55 students). As in the previous question, no students selected the "Other" option, indicating that the response categories were comprehensive and well-aligned with students' usage patterns.

These results indicate that students appear to rely on AI tools to support essential academic tasks, particularly those involving problem-solving and assignment validation. Prior studies have shown that students use AI tools such as ChatGPT to facilitate the comprehension of complex concepts and to solve difficult academic problems [56, 57], and that the integration of ChatGPT can support interactive learning and individualized assistance, fostering students' understanding of complex concepts [58].

By contrast, more specialized or exploratory functions, such as conceptual modeling or graph visualization, were reported less frequently, suggesting that most students engage with AI tools at a practical and procedural level rather than for in-depth conceptual exploration. For example, [59] found that students used AI more often for studying and preparation, and less often for writing, data processing, and graphic creation. Such patterns may reflect the immediate academic demands students face, as well as limited familiarity with the broader capabilities of these tools.

These findings highlight a potential role for educators in expanding students' understanding of what AI mathematics tools can do. Although practical applications remain the dominant mode of use, educators could consider introducing students to advanced features during coursework or tutorials. Doing so may encourage more comprehensive engagement with the tools, supporting not only short-term academic performance but also deeper mathematical thinking and self-directed learning.

Students' Perceptions of AI Math Tools

This section presents and discusses the findings related to Research Objective 3 (RO3), which aimed to examine students' perceptions of AI mathematics tools across four constructs: Perceived Usefulness, Learning Impact, Trust and Value, and Behavioural Intention to Use. Composite scores for each construct were computed by averaging the Likert-scale responses associated with the respective items. Descriptive statistics were then used to summarize the central tendencies of these perception scores. The results are shown in Table 3.

Table 3. Mean and Standard Deviation for Each Perception Construct (n = 340)

Components	PU_avg	LI_avg	TV_avg	BI_avg
Mean	2.99	2.97	2.87	2.65
Standard deviation	0.474	0.510	0.491	0.594

Among the four constructs, Perceived Usefulness recorded the highest mean score (M = 2.99, SD = 0.47), suggesting that students generally agree that AI math tools are beneficial and relevant to their academic needs. This was closely followed by Learning Impact (M = 2.97, SD = 0.51), indicating that students perceive these tools as helpful in improving their understanding and performance in mathematics.

Trust and Value received a moderately positive score (M = 2.87, SD = 0.49), reflecting a fair level of student confidence in the reliability and credibility of AI-based mathematics tools. However, Behavioural Intention to Use recorded the lowest mean score (M = 2.65, SD = 0.59), which suggests a more cautious or selective stance toward continued use at this stage. This interpretation is based on quantitative deduction from the survey data, as no qualitative or open-ended responses were collected to further explain this pattern.

The comparatively lower score for behavioural intention could be attributed to several factors, such as limited awareness of advanced functionalities, reliance on peers for tool recommendations, or uncertainty regarding the long-term benefits of these tools, which aligns with prior studies showing that awareness plays a central role in shaping behavioural intention [60], peer and social influence mediate technology adoption [61], and perceptions of risk and long-term value affect adoption decisions [62-63]. It may also reflect students' caution about becoming overly dependent on AI, especially in foundational mathematics education, as recent studies show concerns about AI dependency among mathematics learners and teachers [64-67].

In summary, the results indicate a generally positive perception of AI math tools in terms of usefulness and learning enhancement, but also reveal an opportunity to strengthen students' commitment to continued use. These findings point to the importance of integrating AI tools more effectively into formal learning environments and providing students with guidance to build sustained trust and intention to use such technologies.

LIMITATIONS

This study acknowledges several methodological limitations. The questionnaire was developed based on the adapted TAM framework, in which two original TAM constructs were retained and two context-specific constructs were introduced. Although the items were newly written or contextually modified for this study and underwent content validation by one expert, no pilot test was conducted prior to full administration. The instrument was subsequently validated through CFA and reliability analysis, which provides statistical support for the measurement model; however, the use of a single expert and the absence of a preliminary pilot stage are recognized as methodological limitations.

CONCLUSION

This study investigated foundation students' engagement with AI math tools by examining their initial awareness, academic usage purposes, and overall perceptions. The findings provide meaningful insights into how students encounter, utilize, and evaluate AI tools within the context of mathematics learning.

In terms of initial awareness (RO1), the majority of students became familiar with AI math tools through informal sources such as peer recommendations and social media. Institutional channels, including schools and educational programs, played a more limited role. This highlights the strong influence of peer networks and digital platforms in shaping students' exposure to educational technologies and points to the need for more proactive efforts by institutions to introduce and promote reliable AI tools through formal means.

Regarding usage purposes (RO2), students primarily used AI tools for practical academic tasks such as solving mathematical problems, checking homework, and understanding new concepts. In contrast, less frequent use of features such as graphing, exploring mathematical theories, and performing complex calculations suggests that student engagement remains focused on procedural support rather than conceptual exploration. This task-oriented approach emphasizes the importance of academic guidance to help students recognize and apply the broader capabilities of AI tools for deeper learning.

Students' perceptions of AI math tools (RO3) were generally positive. Perceived Usefulness and Learning Impact received the highest average scores, indicating that students recognize the academic value of these tools. However, the scores for Trust and Value, and especially Behavioural Intention to Use, were comparatively lower than Perceived Usefulness and Learning Impact, indicating a less certain orientation toward continued use. This may be influenced by limited familiarity with advanced functions, uncertainty about reliability, or concerns about relying too heavily on AI in foundational mathematics learning.

In summary, foundation students show strong awareness and frequent use of AI math tools for key academic tasks. However, their engagement remains largely practical and influenced by informal discovery. There is a clear opportunity for educational institutions to adopt a more structured approach to promoting the ethical, informed, and comprehensive use of AI tools in learning. Encouraging deeper applications and fostering trust and intention to use these technologies may support more meaningful and sustained engagement over time.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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