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Exploring the Use of Conversational AI Tools in Mathematical Problem-Solving among Higher Education Students

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ABSTRACT

This preliminary study examines how higher education students utilize large language models (LLMs), such as ChatGPT, Claude, and Gemini, for solving math problems. As these conversational AI interfaces become more common, understanding their role in mathematical learning is essential. This research examines key aspects of LLM interaction in mathematics, including problem types, prompt engineering, solution presentation and interpretation, solution verification, learning impact, and ethical considerations. Using a structured survey of 34 students across disciplines, we assessed their awareness and usage of LLMs for mathematical tasks. Preliminary findings indicate high awareness and diverse approaches to prompting and solution verification. Students primarily use AI for step-by-step explanations (78.8%) and solution verification (78.8%), with 93.9% reporting increased understanding. However, 84.8% experienced incorrect solutions, highlighting verification challenges. These findings offer valuable insights into student behavior and provide a foundation for developing pedagogical strategies that leverage conversational AI to enhance mathematical learning while addressing its limitations.

1. Introduction

The landscape of educational technology has undergone a profound transformation with the emergence of large language models (LLMs), such as ChatGPT, Claude, and Gemini. These conversational AI tools have democratized access to powerful computational assistance, creating new opportunities and challenges for mathematics education. In this study, several key terms are used to describe the AI tools under investigation. A chatbot refers to a software application designed to simulate human conversation, often used for tasks such as answering questions or providing guidance. Conversational AI is a broader category that includes chatbots and other systems capable of engaging

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in human-like dialogue using natural language. These systems are typically powered by LLMs – advanced AI models trained on vast datasets to understand and generate human-like text. Understanding these terms is essential for interpreting how students engage with these tools in mathematical concepts. Unlike traditional computer algebra systems (CAS), which require specific syntax and commands, LLMs allow students to interact using natural language [1], significantly lowering the barrier to obtaining mathematical assistance. This shift represents a fundamental change in how students can access mathematical support, transitioning from specialized software that requires technical expertise to intuitive, conversational interfaces accessible to all students.

Mathematics education has historically embraced technological innovations, from graphing calculators to specialized software packages [2]. Each technological advancement has brought both promises and concerns, with educators grappling with questions about how to integrate new tools while maintaining mathematical rigor and learning objectives. However, LLMs represent a paradigm shift due to their accessibility, versatility, and ability to not only solve problems but also explain concepts, provide step-by-step solutions, and adapt to the user's level of understanding. This unique combination of capabilities distinguishes LLMs from previous educational technologies and creates unprecedented opportunities for personalized mathematical learning support.

The integration of conversational AI into mathematics education raises important questions about pedagogical practices and student learning outcomes. Traditional concerns about technology in mathematics education, such as the potential for reduced procedural fluency or over-dependence on computational tools, take on new dimensions with LLMs [3]. These tools can provide not just answers but also explanations, making them potentially more educationally valuable yet also more challenging to regulate in academic contexts. The natural language interface of LLMs makes them particularly appealing to students, but this ease of use may mask the complexity of ensuring appropriate and effective utilization for learning purposes.

This shift raises important questions about how students are integrating these tools into their mathematical learning processes and what implications this integration has for the mathematics pedagogy [4]. Current research on LLM use in education has primarily focused on writing assignments and general academic applications, with limited investigation into domain-specific usage patterns, particularly in mathematics. Understanding how students naturally adopt and adapt these tools for mathematical problem-solving is crucial for developing appropriate pedagogical responses and institutional policies.

This preliminary study aims to investigate the emerging patterns of LLM use among higher education students, specifically for mathematical problem-solving. We explore the types of mathematical problems students present to these systems, how they formulate their prompts, how they interpret and verify the provided solutions, and how these interactions may impact their understanding of mathematics. Additionally, we examine the ethical considerations and challenges that arise as students navigate the appropriate use of these powerful tools in academic contexts. By focusing on actual usage patterns rather than theoretical possibilities, this study provides empirical evidence to inform educational practice and policy development.

By focusing on actual usage patterns rather than theoretical possibilities, this study provides empirical evidence to inform educational practice and policy development. The insights gained will contribute to the development of pedagogical approaches that effectively incorporate LLMs as learning aids rather than answer generators. This study seeks to answer the following research question: How do higher education students utilize conversational AI tools powered by LLMs for mathematical problem-solving, and what are the pedagogical implications of their usage patterns, verification strategies, and perceived learning impact?

2. Literature Review

2.1 Technological Tools in Mathematics Education

The integration of technology into mathematics education has a long and evolving history. Research by Artigue [3], Hoyles [5] has documented how various computational tools have transformed mathematical teaching and learning practices. CAS such as Mathematica, Maple, and MATLAB have been extensively studied [6-9], highlighting both benefits, including improved visualization and computational capabilities, but also concerns about potential diminishment of procedural fluency.

2.2 The Emergence of LLMs in Education Contexts

LLMs represent a significant technological advancement over previous educational technologies due to their natural language processing capabilities and broad knowledge base. Unlike specialized mathematical software, LLMs can understand problems posed in natural language, provide explanations at various levels of detail, and adapt their responses based on follow-up questions [10,11]. Early research on LLM use in education has focused on writing assignments [12,13], ethical considerations [14,15], and the detection of AI-generated content [16-19]. However, research specifically examining how students use LLMs for mathematical problem-solving remains limited.

2.3 Research Gap

While existing research has examined LLMs in a general educational context, particularly in writing and ethics. There is a notable lack of empirical studies focusing on their application in mathematics education. Specifically, little is known about how students formulate prompts, verify AI-generated solutions, and perceive the learning impact of these tools in mathematical problem solving. This study addresses this gap by providing data-driven insights into student usage patterns and pedagogical implications.

3. Methodology

This study employed a quantitative survey-based approach to investigate how higher education students utilize LLM AI tools for mathematical problem-solving. A cross-sectional survey design was implemented to capture students' experiences, behaviors, and perceptions regarding LLM use for mathematical tasks at a specific point in time. This design was chosen as it allows for the collection of standardized data across diverse participants while providing insights into current usage patterns and attitudes toward conversational AI in mathematics education [20].

Several methodological limitations should be acknowledged. The convenience sampling approach and relatively small sample size limit generalizability to broader student populations. The self-reported nature of the data may be subject to recall bias and social desirability effects. Additionally, the cross-sectional design captures usage patterns at a single time point, which may not reflect the dynamic nature of AI tool adoption and learning processes.

3.1 Survey Instrument

The survey instrument was structured into seven comprehensive sections: demographics and awareness, usage patterns, question formulation, solution interpretation and verification, learning impact, ethical considerations, and overall experience. The survey design was informed by existing literature on technology adoption in education [21] and mathematical problem-solving behaviors [22].

Content validity was established through expert review involving three faculty members with expertise in mathematics education and educational technology. The reviewers evaluated each survey item for relevance, clarity, and alignment with research objectives. Based on their feedback, several questions were refined for clarity, and additional response options were included to ensure comprehensive coverage of potential student experiences.

Face validity was assessed through pilot testing with five graduate students who provided feedback on question comprehensibility and survey flow. Minor adjustments were made to improve question wording and response option clarity based on their suggestions. While full psychometric validation was beyond the scope of this preliminary study, these validation steps help ensure the instrument’s appropriateness for capturing the intended constructs.

The survey’utilized a combination of Likert-scale items, multiple-choice selections, and categorical response options to facilitate quantitative analysis. Several questions allowed for multiple response selection to comprehensively capture the range of student experiences.

3.2 Sample Size

The sample size for this preliminary study was determined based on resource constraints and the exploratory nature of the research. No fixed sample size is universally “enough” for internet survey research, where the response rates may be low [23]. While a formal power analysis was not conducted due to the lack of prior effect size estimates in this emerging field, the target sample size of 30-35 participants aligns with recommendations for pilot studies in educational research [24]. The achieved sample of 34 participants meets the minimum threshold for meaningful statistical analysis while acknowledging the limitations inherent in a convenience sampling approach.

3.3 Participants

A total of 34 students completed the survey, recruited through convenience sampling from higher education institutions in Malaysia. The eligibility criteria for participation included: (1) current enrolment in higher education programs with mathematical components, (2) basic familiarity with digital technologies and internet access, (3) voluntary consent to participate in the research, and (4) ability to complete the survey in English. Participants represented various academic levels (undergraduate and postgraduate) and disciplines, including engineering, computer science, mathematics, and sciences that incorporate mathematical problem-solving. The diverse disciplinary representation was intentionally sought to capture varied perspectives on LLM use across different mathematical contexts.

No specific exclusion criteria were applied beyond the eligibility requirements, and no participants dropped out during the survey completion process, resulting in a 100% response rate among those who initiated the survey. The convenience sampling method was employed due to accessibility and time constraints, though this approach limits the generalizability of findings to broader student populations.

3.4 Data Analysis

Given the small sample size, the analysis focused on identifying patterns and relationships through frequency counts, cross-tabulations, and visual summaries. Frequency counts were used to determine how often each response option was selected, providing a basic understanding of response distribution. Cross-tabulation was applied to explore potential relationships between key variables, such as demographic characteristics and response patterns. This helped to identify any notable trends or associations, even within a limited dataset. For multi-select questions, the percentage of respondents selecting each option was calculated based on the total number of participants, rather than the total number of selections. This method ensured that the analysis accurately reflected the proportion of individuals endorsing each response. Visual representations were included for a clearer understanding of the findings. These visuals were created using Google Sheets and were chosen to highlight key insights in a clear and accessible manner. Due to the limited data size, no inferential statistical tests were conducted, and the emphasis remained on descriptive exploration and visual representation of the data.

4. Results

4.1 Awareness and Adoption

Results strongly suggest high familiarity with AI chatbots among respondents. Almost 88% rated their familiarity as either "Familiar" or "Very Familiar" with AI chatbots like ChatGPT, DeepSeek, Claude, or Google Gemini. All respondents have used at least one listed AI chatbot, with ChatGPT standing out as universally used, followed by Google Gemini and Microsoft Bing Chat/Copilot (Figure 1).

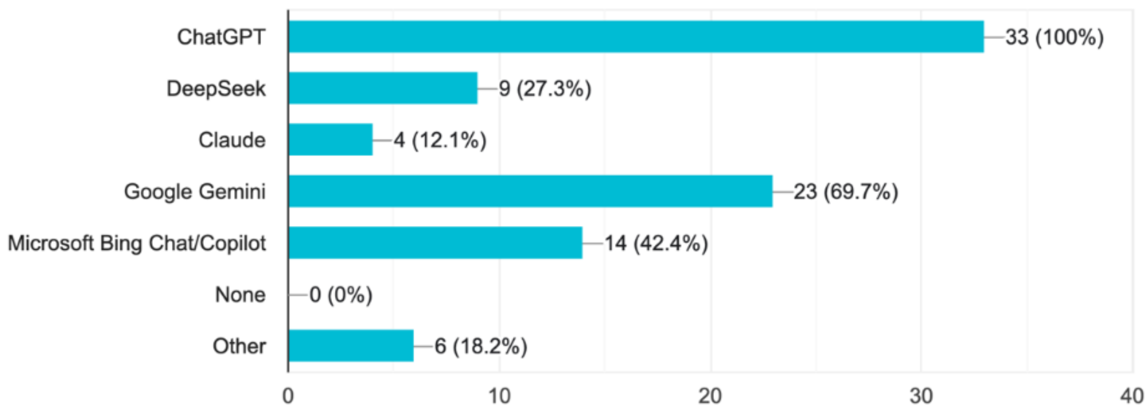

Fig. 1. AI chatbot familiarity

4.2 Usage Patterns

A substantial majority (50%) utilize AI for math-related tasks at least 1-6 times weekly. Calculus (69.7%) stands out as the most common area where users seek AI help, followed by statistics/probability, linear algebra, and differential equations, as shown in Figure 2. This reflects the complex nature of these advanced mathematical subjects. Regarding problem-solving stages, "Finding solution approaches" and "Checking my work" both received 78.8% responses, indicating AI's dual role in both guidance and verification. Users also frequently employ AI for understanding problem statements (57.6%) and explaining difficult concepts (69.7%) (Figure 3).

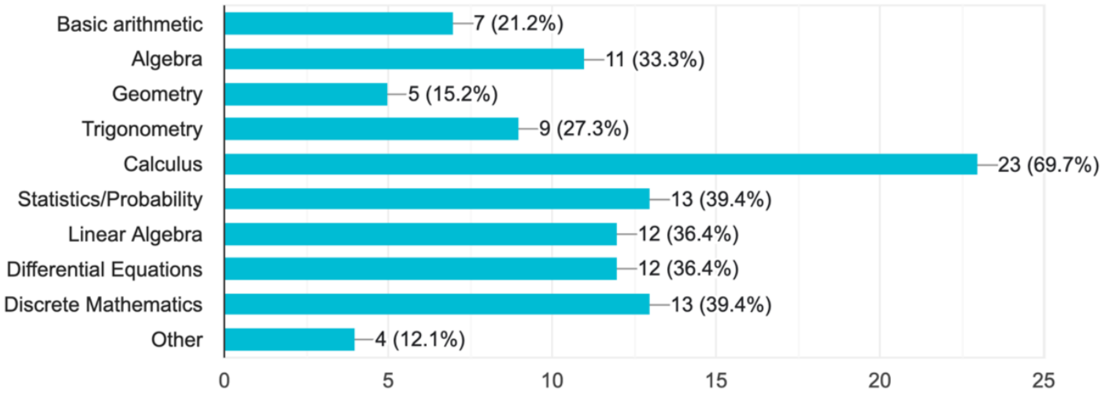

Fig. 2. The types of mathematical problems

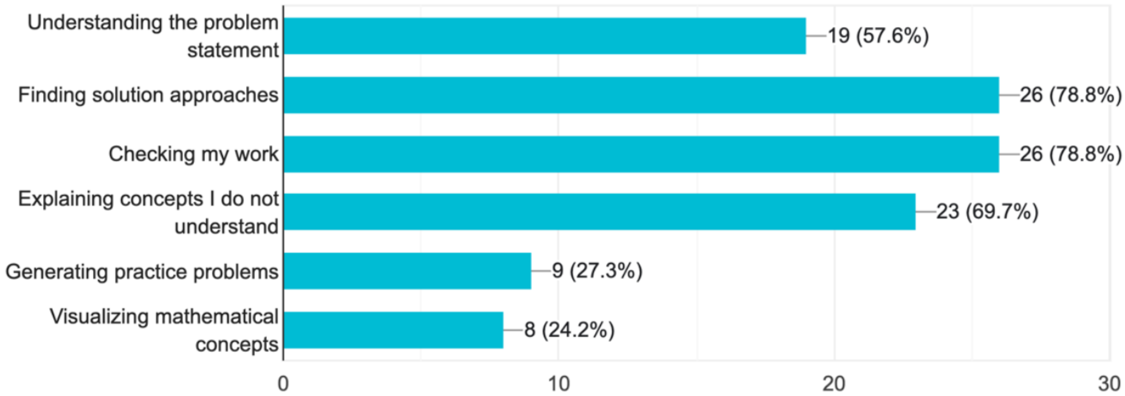

Fig. 3. The stage of problem-solving

4.3 Questions Formulation

Copy and paste the exact problem statement was selected by 73.5% of respondents, representing the dominant method. This suggests most users prefer providing AI with problems precisely as written, assuming this leads to the most accurate response. For improving AI responses (Figure 4), explicitly asking for step-by-step solutions was the most popular approach (84.8%), followed by requesting explanations of key concepts first (51.5%). This indicates a strong desire to understand the process, not just the final answers.

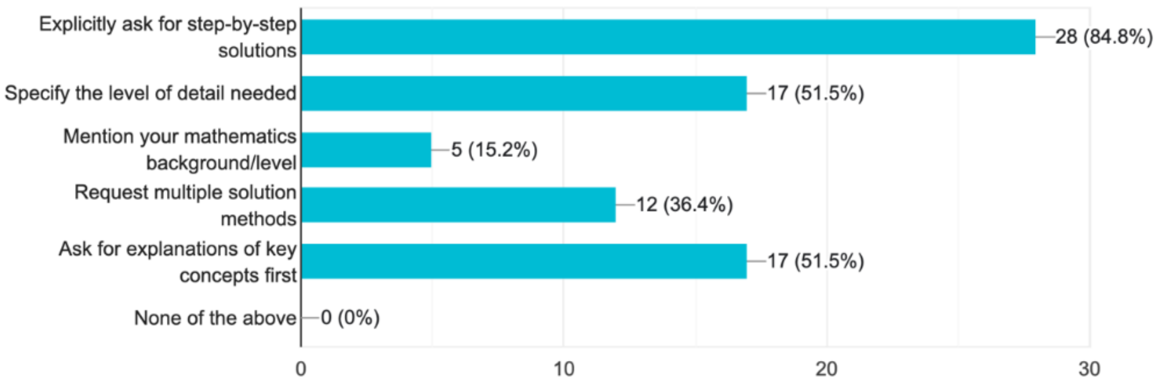

Fig. 4. Strategies to get responses

4.4 Solution Verification

The most popular verification method is cross-checking with textbook solutions (81.8%), followed by asking peers/instructors (66.7%) and working through problems themselves (66.7%). Notably, 39.4% verify with another AI chatbot, while only 6.1% directly trust AI without checking (Figure 5). Regarding confidence in assessing AI solutions, 61.8% report moderate confidence (level 3 on a 5-point scale), with 23.5% somewhat high confidence. This moderate confidence suggests healthy skepticism toward AI outputs. However, 84.8% experienced incorrect solutions, highlighting verification challenges as in Figure 6.

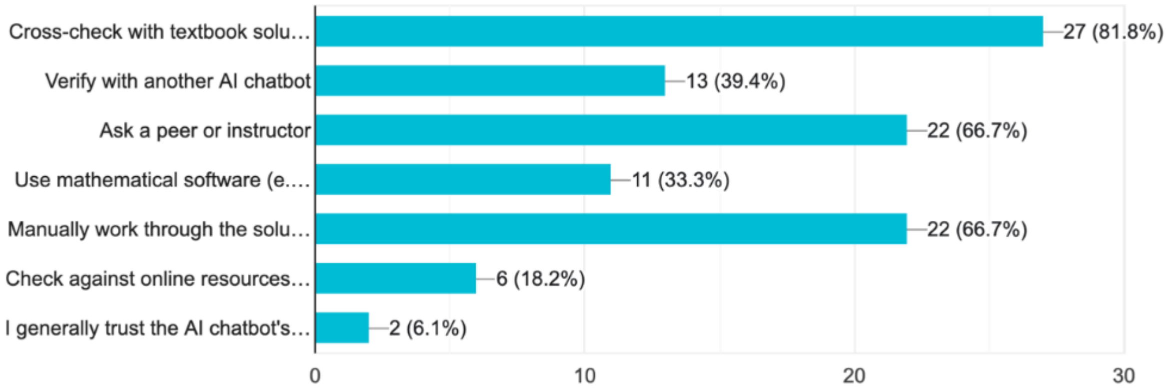

Fig. 5. Solution verification

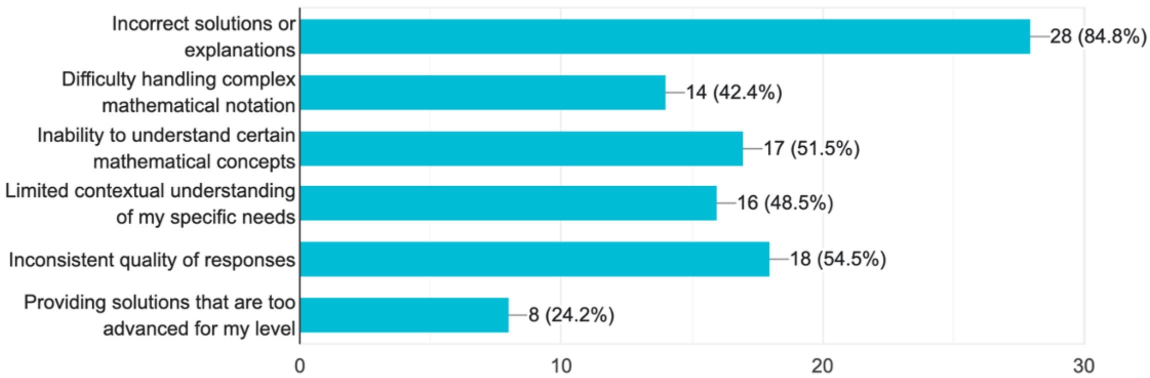

Fig. 6. Challenges using AI Chatbot/solvers

4.5 Learning Impact

Results show overwhelmingly positive perceived impact: 69.7% report AI "slightly increased understanding" and 24.2% report "significantly increased understanding," totaling 93.9% reporting some increased understanding. Students primarily use AI explanations to clarify specific steps they did not understand (75.8%), to understand basic concepts (69.7%), and to gain deeper insights beyond lectures (54.5%), as shown in Figure 7. Most respondents (57.6%) work through each step alongside AI explanations rather than passively consuming answers.

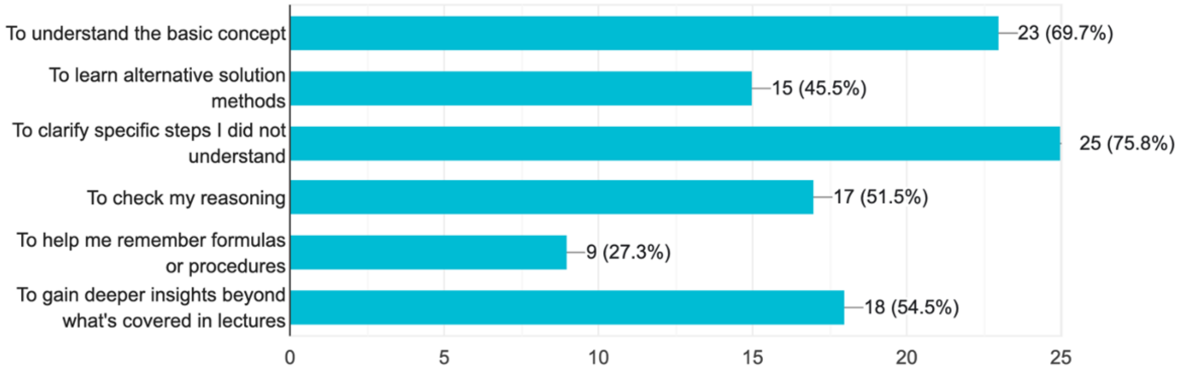

Fig. 7. Learning impact

4.6 Ethical Consideration

Primary ethical concerns include over-reliance on technology (82.4%), academic dishonesty (67.6%), and potential erosion of fundamental skills (41.2%) (Figure 8). These findings suggest the need for careful consideration of ethical implications in AI integration.

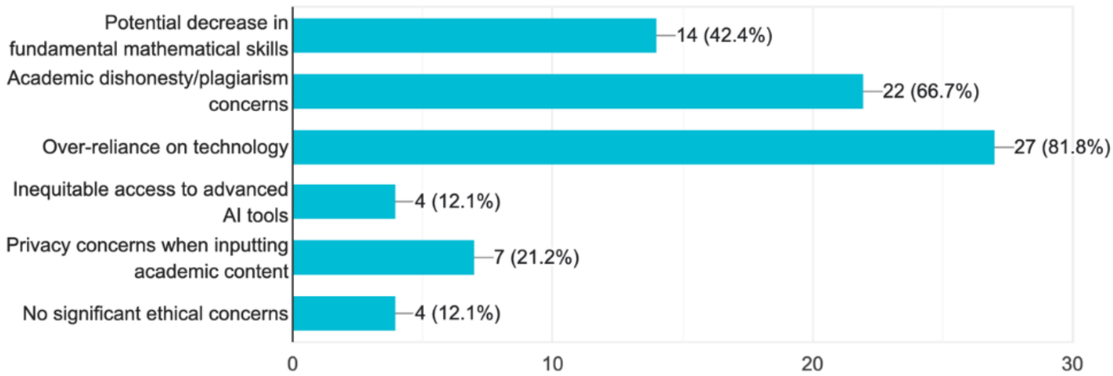

Fig. 8. Ethical concern

4.7 Overall Experience

The most valued benefits as in Figure 9, include step-by-step explanations (78.8%) and immediate feedback/assistance (66.7%). Students seek more accurate solutions to complex problems (63.6%) and more interactive problem-solving guidance (60.6%).

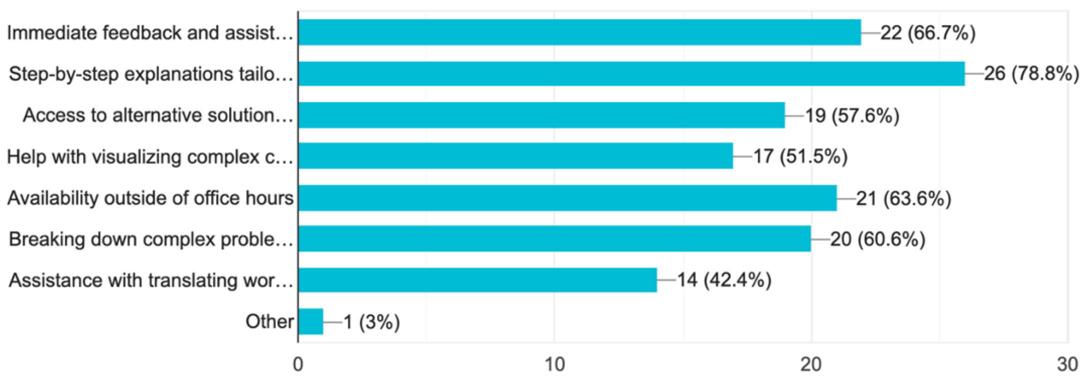

Fig. 9. How AI chatbots support mathematics learning

5. Discussion

This preliminary study aimed to investigate the emerging patterns of LLM use among higher education students, specifically examining how they utilize conversational AI tools for mathematical problem-solving. The research explored key dimensions of AI-mathematics interaction, including problem types, prompt engineering approaches, solution presentation and verification methods, learning impact perceptions, and ethical considerations surrounding AI use in academic contexts.

5.1 Adoption and Usage Patterns

Our results indicate high awareness and adoption of conversational AI tools among higher education students, aligning with diffusion of innovation theory. The grassroots nature of discovery through peers and social media, rather than formal educational channels, presents both challenges and opportunities for institutions developing coherent policies. Students apply conversational AI across diverse mathematical domains, particularly in challenging areas like calculus. Unlike specialized CAS that primarily perform computations, LLMs serve broader roles as learning companions, concept explainers, and problem-solving guides.

5.2 Prompt Engineering as a Mathematical Skill

The emergence of prompt engineering as a new mathematical skill requires not only mathematical understanding but also metacognitive awareness and communication precision [23-25]. This represents a natural extension of mathematics education's historical emphasis on precise communication, but with new considerations specific to human-AI interaction.

5.3 Verification Challenges and Opportunities

The high percentage (84.4%) reporting experiences with incorrect AI solutions highlights critical tensions in using these tools. However, the verification strategies demonstrate varying levels of mathematical sophistication and may foster deeper mathematical engagement as students must critically evaluate solutions rather than passively accepting them.

5.4 Learning Impact and Pedagogical Implications

The strong appreciation for step-by-step explanations suggests these tools may be particularly valuable for procedural learning and scaffolding complex problem-solving processes. However, solution accuracy challenges raise concerns about potential negative learning impacts if students internalize incorrect approaches. The desire for interactive problem-solving guidance indicates students value conversational AI as learning companions rather than mere answer providers, aligning with Vygotskian perspectives on scaffolded learning [26].

5.5 Implications for Mathematics Pedagogy

Several significant implications emerge from this study for mathematics pedagogy and curriculum development. First, the need for AI-aware mathematics instruction has become evident, requiring educators to explicitly address effective and ethical AI tool use. This includes developing guidance on prompt formulation, solution verification, and appropriate contexts for AI assistance. The integration of prompt engineering as a mathematical communication skill represents a new curricular consideration that warrants systematic development.

Second, the emphasis on verification skills must be strengthened in mathematics instruction. Given the accuracy challenges with AI-generated solutions, mathematics curricula should place increased emphasis on solution verification methods, equipping students with robust strategies to critically evaluate AI-generated content. This represents an opportunity to enhance mathematical reasoning skills while addressing practical challenges of AI integration.

Third, assessment approaches may require significant reconsideration to emphasize mathematical reasoning and conceptual understanding rather than solution production alone. Traditional assessment methods that focus primarily on final answers may become less relevant in an AI-rich environment, suggesting the need for assessments that evaluate process understanding, reasoning quality, and verification skills.

Finally, AI literacy should be recognized as an emerging form of mathematical competency requiring explicit curriculum development. The skills needed for effective AI interaction in mathematical contexts—including prompt formulation, output evaluation, and integration with traditional problem-solving approaches—represent new areas of mathematical literacy that warrant systematic instruction and assessment.

5.6 Limitations and Future Research

Several important limitations must be acknowledged in interpreting these findings. The convenience sampling approach and relatively small sample size (n=34) limit generalizability to broader student populations, particularly those from different cultural, economic, or educational contexts. The sample's high level of technology familiarity may not be representative of all higher education students, potentially overestimating adoption rates and usage sophistication.

The self-reported nature of the data introduces potential bias through social desirability effects and recall inaccuracy. Students may overreport positive learning impacts or underreport problematic usage patterns due to perceived expectations or memory limitations. Additionally, the cross-sectional design captures usage patterns at a single time point, which may not reflect the dynamic nature of AI tool adoption and evolving usage practices as students gain more experience with these technologies.

Future research directions may include longitudinal impact assessment of AI use on mathematical understanding, comparative effectiveness research between different AI integration approaches, the development of prompt engineering pedagogy, and the investigation of an effective verification strategy instruction.

The rapid evolution of AI technology means that findings may quickly become dated as new tools and capabilities emerge. The study also does not account for institutional variations in AI policies or technology access that may influence usage patterns. Finally, the study did not examine longer-term implications of AI use on mathematical skill development or academic performance, representing important areas for future investigation.

6. Conclusion

This preliminary investigation suggests conversational AI technologies have significant potential to enhance mathematical learning when used thoughtfully, but also present challenges requiring careful navigation. The most promising path forward appears to be thoughtful integration, positioning conversational AI as a complement to effective mathematics instruction—powerful aids that enhance explanation and provide support while preserving essential cognitive processes underlying genuine mathematical understanding. Students demonstrate agency in their technological use through active verification and critical evaluation, suggesting they are not passive consumers but engaged learners. The strong emphasis on detailed, step-by-step explanations and interactive guidance underscores the pedagogical value of these tools when effectively integrated into learning environments. By developing appropriate pedagogical approaches, institutional policies, and student guidance, mathematics educators can help ensure these powerful tools serve to deepen rather than diminish mathematical learning. Ongoing research and dialogue among educators, students, and technology developers will be essential to realizing the full potential of conversational AI in mathematics education.

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