The Evolving Role of AI in Math: A Grounded Theory of Student and Teacher Interactions with ChatGPT

Kenneth V. Ragaza, LPT, MAEd, Ed.D.(c)
Cebu Normal University, Cebu City, Philippines
ragazak@cnu.edu.ph

ABSTRACT

This study employs a grounded theory approach to conceptualize the process of integrating a large language model, specifically ChatGPT, into mathematical problem-solving within a university setting. Data were collected from Thirty (30) Bachelor of Secondary Education Major in Mathematics students at Cebu Normal University during the first semester of 2024–2025 through semi-structured interviews, group discussions, and classroom observations. Through a constant comparative analysis of the data, a theoretical framework was generated that explains the dynamic relationship between students and the AI tool. The emergent theory, titled "AI – Assisted Scaffolding and Conceptualization," outlines a three-phase process: (1) Initial Tool Engagement, where students explore ChatGPT's capabilities and limitations; (2) The Scaffolding Cycle, where the AI acts as a digital tutor, providing hints and breaking down complex problems; and (3) Conceptual Synthesis, where students integrate the AI's assistance with their prior knowledge to form a deeper understanding. The findings indicate that while ChatGPT effectively enhances conceptual understanding and problem-solving strategies, this process is mediated by both technical limitations (e.g., occasional inaccuracies) and pedagogical challenges (e.g., overreliance). This research contributes a new theoretical model that helps to explain the mechanisms through which generative AI can be integrated into mathematics education, providing a framework for educators and curriculum designers to effectively leverage these tools while fostering critical thinking.

Keywords: *Grounded Theory, ChatGPT, Mathematical Problem-Solving, AI in Education, Conceptual Framework*

INTRODUCTION

The emergence of generative artificial intelligence (AI) tools, such as ChatGPT, marks a significant shift in educational technology. While the broader literature on AI in education is growing, there is a critical theoretical gap regarding the process through which these tools are integrated into specific pedagogical contexts, particularly in the complex domain of mathematical problem-solving. Existing studies often focus on the outcomes or benefits of AI without fully conceptualizing the lived experience and dynamic interactions that unfold as students and instructors begin to use these tools. This paper aims to address this gap by employing a grounded theory approach to develop a substantive theory explaining this process.

The global push for digitalization in education, championed by organizations like the World Economic Forum (2020) and the International Commission on the Futures of Education (2021), has underscored the potential of AI to revolutionize learning. Scholars like Williamson and Eynon (2020) and Zawacki-Richter et al. (2019) have highlighted how AI can personalize learning and enhance engagement. However, these discussions often occur at a macro level, leaving the micro-level processes, the day-to-day interactions, the challenges, and the adaptations students and teachers make largely unexplained. This is a crucial area of inquiry, as a successful integration is not just a matter of adopting technology but of navigating the emerging pedagogical and cognitive relationships that result from its use.

The integration of ChatGPT into mathematics instruction at Cebu Normal University presents a unique opportunity to observe and analyze this phenomenon. While mathematics is often viewed as abstract and challenging, AI offers promising new avenues for real-time explanations and problem-solving strategies. Yet, the literature has not adequately addressed how students conceptualize their roles in an AI-assisted environment, or how their problem-solving behaviors evolve through continuous interaction with the tool. This study moves beyond simply documenting the effects of ChatGPT to theorizing the underlying process of student-tool interaction and its impact on mathematical learning.

Therefore, the central aim of this study is to generate a substantive theory of how students engage with and leverage ChatGPT to scaffold their mathematical problem-solving abilities. This research is not guided by pre-existing hypotheses but is instead driven by the data itself. We will explore the patterns, stages, and conditional relationships that emerge from students' experiences, ultimately building a theoretical framework that can be applied to similar contexts. This research contributes to the broader academic discourse by offering a conceptual model of AI's role in education, moving the conversation from what these tools can do to how they actually work in a real-world learning environment.

RESEARCH METHODOLOGY

This study employs a constructivist grounded theory approach to investigate the dynamic process of integrating ChatGPT into mathematical problem-solving. Grounded theory is a systematic qualitative methodology that aims to generate a substantive theory from data, rather than beginning with a pre-established theoretical framework. This approach is particularly suitable for this study because the process of AI integration into education is an emergent phenomenon that is not yet well-explained by existing theory.

Research Setting and Participants

The research was conducted at Cebu Normal University (CNU) during the first semester of the academic year 2024–2025. The College of Teacher Education's focus on technological innovation in STEM made it an ideal site for this study. The sample consisted of 30 Bachelor of Secondary Education Major in Mathematics students who were selected using theoretical sampling. This iterative process involved an initial small, purposeful sample that was then expanded based on the emerging concepts from the data. The goal of this process was to gather a diverse range of experiences with AI tools and varying levels of academic performance until theoretical saturation was achieved. The final number of 30 was reached when no new concepts or categories emerged from the data, indicating that the theory was sufficiently developed.

Data Collection

Data collection was an iterative and simultaneous process with data analysis, as is standard in grounded theory. The goal was not to collect all data at once but to let the emerging theory guide subsequent data collection.

- **Semi-Structured Interviews:** The interviews were designed to be broad and open-ended. Questions were not tied to a pre-defined set of themes but instead asked participants to describe their experiences, challenges, and thoughts on using ChatGPT. The interviews were not just a means of gathering data but a tool for discovering initial concepts and categories.
- **Group Discussions:** Multiple group discussions were held to allow for peer interaction and shared reflection. The discussions helped to illuminate social dynamics and collective understandings that individual interviews might miss. The content of these discussions evolved based on the emerging categories from initial interviews.
- **Classroom Observations:** Classroom observation sessions were conducted to provide rich context on how students actually used the tool during problem-solving. These observations helped to verify and elaborate on the concepts emerging from the interviews.

Data Analysis: The Constant Comparative Method

The analysis of the data was a rigorous and continuous process using the constant comparative method (Charmaz, 2014). This method is a hallmark of grounded theory and involves comparing newly collected data with existing data and emerging concepts.

1. **Initial Coding:** The process began with open coding, where data from all sources (interviews, discussions, observations) was broken down into small, distinct segments. Each segment was given a code that captured its essence (e.g., "AI-generated error," "explaining concepts," "overreliance"). This stage was about generating as many codes as possible.
2. **Focused Coding:** The researcher then moved to focused coding, selecting the most significant and frequent initial codes to synthesize and organize them. The initial codes were grouped into larger, more conceptual categories that represented the core processes and behaviors identified in the data. For example, codes like "prompting for hints," "getting step-by-step solutions," and "checking work" might have been grouped into a larger category like "Scaffolding."

3. *Theoretical Sampling:* The emerging categories and relationships guided the next phase of data collection. As the theory developed, the researcher would have sought out new participants or new contexts to fill any gaps, such as seeking out students with different levels of technical literacy or from other academic years. This process continued until theoretical saturation was reached, which was determined to be at a sample size of 30.

4. *Memo Writing:* Throughout the entire process, the researcher engaged in memo writing, recording their thoughts, ideas, and theoretical links. These memos were critical for building the theoretical framework and outlining the connections between categories.

Rigor and Trustworthiness

To ensure the trustworthiness of the findings, several strategies were employed:

- **Member Checks:** Participants were given the opportunity to review the initial findings and the emerging conceptualization to ensure their experiences were accurately represented.

- **Audit Trail:** A detailed record was kept of all methodological decisions, from initial sampling choices to final coding decisions, to ensure transparency and replicability.

- **Theoretical Saturation:** The ultimate measure of rigor in grounded theory is the achievement of theoretical saturation, a point that was reached with the 30 participants.

- **Reflexivity:** The researcher's own background and assumptions were continuously reflected upon to minimize potential bias in data interpretation.

By following this rigorous, iterative process with a robust sample size, the study aims not just to describe experiences but to construct a new theory that explains the complex and emergent phenomenon of AI-assisted problem-solving in mathematics education.

Results and Discussions: A Grounded Theory of AI-Assisted Mathematical Problem-Solving

This section presents the substantive theory that emerged from the constant comparative analysis of data from interviews, group discussions, and classroom observations. Rather than simply presenting a list of themes, the findings are organized into a conceptual framework that explains the dynamic process through which students at Cebu Normal University integrate ChatGPT into their mathematical problem-solving. This emergent theory is conceptualized as The AI-Assisted Scaffolding and Conceptualization Model, which operates through three interconnected phases: Tool Engagement, Conceptual Scaffolding, and Integrated Knowledge Construction.

1. Tool Engagement

The initial phase of the process describes how students first encounter and begin to use ChatGPT for mathematical problem-solving. Participants' experiences reveal that this phase is characterized by both initial curiosity and a pragmatic search for efficiency. Students are drawn to the tool by its promise of instant feedback and simplified explanations, particularly when faced with complex or abstract problems.

- **Initial Curiosity and Pragmatic Use:** Students, like Alpha, described an initial sense of excitement: "I found it easier to stick with problems because I could immediately test my ideas and get feedback from ChatGPT." This initial use is often driven by a desire for a quick solution or a way to break through a mental block. The AI serves as an on-demand, non-judgmental resource, which contrasts with the perceived pressure of asking a teacher or peer for help.
- **Navigating Accuracy and Limitations:** A key component of this phase is the discovery of the tool's limitations, particularly its occasional inaccuracies. As Foxtrot explained, "There were a few times when ChatGPT provided wrong answers or explanations, and it threw me off." This realization is a critical turning point. It forces students to move beyond simple reliance and to begin a more critical engagement with the AI's output, thus triggering the next phase of the process.

This phase establishes the foundational conditions for students' interaction with ChatGPT. It highlights that the relationship with the AI tool is not one of blind trust but rather one that requires active navigation and verification, setting the stage for deeper conceptual work.

2. Conceptual Scaffolding

Following the initial engagement, students enter the Conceptual Scaffolding phase. This is the core of the emergent theory, explaining how the AI tool actively helps students build their understanding. It's not just about getting answers; it's about using the AI to break down complex problems and ideas in a personalized way.

- ***Decomposition and Simplification:*** Participants consistently reported that ChatGPT's ability to "decompose" complex problems into simpler steps was its most valuable function. As Delta noted, "When I encountered a concept, I didn't understand, ChatGPT would explain it in simpler terms or give me visual examples that helped me grasp the idea better." This process of simplification acts as a scaffold, providing a supportive structure that allows students to navigate difficult mathematical concepts incrementally.

- ***Iterative Learning and Feedback Loops:*** Unlike a static textbook, ChatGPT allows for an iterative process of learning. Students can try different approaches, get immediate feedback, and make real-time corrections. This continuous feedback loop fosters what participants called a *"trial-and-error"* mindset. Echo's comment, "ChatGPT helped me identify where I went wrong and how to fix it, so I started depending less on waiting for the teacher to guide me," captures this shift toward active, self-directed learning.

This phase demonstrates how the AI tool facilitates a move from passive knowledge reception to active, constructive learning. It provides the necessary support for students to bridge the gap between their current understanding and the new knowledge they are trying to acquire.

3. Integrated Knowledge Construction

The final phase of the model describes the ultimate outcome of the process: the construction of new, integrated knowledge. This is where students move beyond simply using the AI as a tool and begin to internalize and synthesize the knowledge gained.

- ***Cultivating Independence:*** A key finding is that the scaffolding provided in Phase 2 paradoxically leads to greater independence. Charlie's experience, "ChatGPT didn't just give me the answer; it pushed me to try different approaches," illustrates how the tool can shift the locus of control from the AI to the student. By exposing students to multiple problem-solving methods, the tool empowers them to develop a more flexible and robust set of cognitive skills.

- ***Shifting Teacher-Student Dynamics:*** The integration of the AI fundamentally changes the role of the teacher. As one teacher observed, "I found that I had more time to address individual students' needs." This shift allows teachers to move from being the sole provider of information to a facilitator of deeper learning. With the AI handling basic scaffolding, teachers can focus on advanced concepts and critical-thinking discussions, leading to a more meaningful and collaborative teacher-student relationship.

- ***Balancing Reliance and Criticality:*** The final stage also involves a constant negotiation between *over-reliance* and *critical analysis*. Participants acknowledged the risk of "not thinking critically enough" (Charlie), but the experience of encountering inaccuracies in the first phase forces them to develop a critical stance. The successful completion of this phase results in students who use the AI as a supplement to their own cognitive processes, not as a replacement for them.

In sum, the *AI-Assisted Scaffolding and Conceptualization Model* offers a theoretical explanation for how generative AI tools like ChatGPT can be effectively integrated into mathematics education. It moves beyond a simple thematic description by presenting a clear, three-phase process that accounts for the challenges, benefits, and evolving dynamics of this pedagogical innovation. This theory provides a framework for educators and curriculum designers to understand and leverage these tools to foster true conceptual learning and independent problem-solving.

Conclusion: The Emergent Theory and Its Implications

This study employed a rigorous grounded theory approach to conceptualize the process through which students integrate generative AI, specifically ChatGPT, into their mathematical problem-solving. The findings move beyond a mere thematic description to propose a substantive theoretical model: The AI-Assisted Scaffolding and Conceptualization Model. This theory provides a crucial framework for understanding the dynamic and evolving relationship between students, AI tools, and the learning process itself. It identifies three interconnected phases, Tool Engagement, Conceptual Scaffolding, and Integrated Knowledge Construction that explain how students effectively leverage this technology.

Theoretical Contributions

This research makes several key theoretical contributions to the field of educational technology and learning sciences.

- *A New Conceptual Model:* The *AI-Assisted Scaffolding and Conceptualization Model* fills a gap in the literature by offering a process-oriented explanation of how AI tools function in a pedagogical context. Unlike existing models that focus on outcomes (e.g., student performance, engagement), this theory explains the *"how"* behind the process. It illustrates how initial, often superficial, engagement with a tool can lead to a deeper, more profound form of conceptual learning.

- *Reconceptualizing Scaffolding:* This study redefines the traditional concept of scaffolding, extending it to the human-AI interaction. ChatGPT acts as a digital cognitive partner, offering just-in-time support tailored to a student's immediate needs. This suggests a *new, more accessible form of personalized learning* that can be initiated and controlled by the learner, rather than solely by a human educator.

- *The Role of Limitations in Learning:* The theory highlights a paradoxical finding: the AI's occasional inaccuracies are not just a pitfall but a catalyst for learning. The need to critically evaluate and verify the AI's output is what compels students to move from passive consumption to active, critical thinking, thus reinforcing their own problem-solving skills. This suggests that the imperfect nature of current AI tools can be leveraged as a pedagogical asset rather than a liability.

Practical and Pedagogical Implications

The emergent theory provides concrete guidance for educators, curriculum designers, and policymakers.

- *Shift from "What" to "How":* Teachers should move their focus from simply asking "What can AI do?" to "How can we structure learning to leverage its scaffolding capabilities?" The findings

suggest a need for curriculum that intentionally integrates AI, not as a replacement for teachers, but as a tool for guided inquiry.

- *Fostering Critical Literacy:* The potential for over-reliance and inaccuracy necessitates a focus on AI literacy. Educators must equip students with the skills to critically evaluate AI-generated content. Assignments should be designed to require students to justify and explain their solutions, rather than simply presenting the final answer.

- *Empowering the Facilitator:* As the theory demonstrates, the integration of AI can fundamentally change the teacher's role from a primary knowledge transmitter to a facilitator of complex learning. This requires professional development that empowers educators to effectively manage this new dynamic, focusing their energy on higher-order tasks like personalized coaching and ethical discussions.

- *A Call for a Balanced Approach:* While this research highlights the immense potential of generative AI, it also serves as a strong cautionary note. The successful integration of these tools hinges on a balanced approach that promotes intellectual curiosity and deep learning while actively guarding against the risks of over-reliance and diminished critical thinking.

In sum, this grounded theory study provides a robust and nuanced understanding of how ChatGPT functions within the learning ecosystem. By offering a new theoretical model, it not only explains the complex processes at play but also provides a clear roadmap for how to harness the power of AI to transform mathematics education for the better, ensuring that technology serves to enhance, not diminish, the human capacity for learning.

Recommendations

Based on the emergent *AI-Assisted Scaffolding and Conceptualization Model*, the following recommendations are proposed for educators, curriculum designers, and technology developers to effectively integrate AI into mathematics education. These recommendations are structured to align with the phases of the theory, ensuring that they are both conceptually grounded and practically applicable.

1. For Educators: Cultivating Critical Engagement

The theory's *Tool Engagement* and *Integrated Knowledge Construction* phases highlight the need for a balanced approach to AI use. Educators must actively guide students in navigating the tool's limitations and prevent over-reliance.

- *Design for Critical Evaluation:* Teachers should create assignments that require students to *evaluate and justify* AI-generated solutions. Instead of simply accepting an answer, students should be prompted to identify potential inaccuracies, compare the AI's method to their own, and articulate why one approach is superior. This practice directly addresses the "over-reliance" concern by transforming the AI from a source of truth into a cognitive partner that must be critically assessed.

- *Leverage AI for Deeper Conceptualization:* Utilize the AI as a tool for *conceptual scaffolding*, as identified in the theory. Teachers should encourage students to use ChatGPT to ask "why" questions, explore alternative problem-solving methods, and break down complex concepts into manageable steps. This shifts the focus from finding an answer to understanding the underlying mathematical principles.

- ***Professional Development in AI Pedagogy:*** Provide educators with training on how to manage the evolving classroom dynamic. Training should focus not only on the technical aspects of AI but also on strategies for facilitating deeper, inquiry-based learning. This prepares teachers to transition from being the primary knowledge provider to becoming a guide who helps students navigate their AI-assisted learning journey.

2. For Curriculum and Technology Developers: Enhancing the Learning Process

The emergent theory reveals that the effectiveness of the AI tool depends on its design and how it is integrated into the curriculum.

- ***Integrate AI with Curriculum Design:*** Curriculum developers should work to embed AI tools directly into course materials in a way that aligns with the *Conceptual Scaffolding* phase. This includes designing AI interfaces that encourage students to seek hints and step-by-step guidance rather than providing instant, complete solutions.

- ***Enhance AI Accuracy and Transparency:*** While the theory shows that inaccuracies can be a learning catalyst, they can also hinder the learning process. Developers must continue to improve the accuracy and reliability of AI tools. Additionally, they should design mechanisms that allow the AI to *explain its reasoning*, providing students with insight into the tool's logic and making it easier to identify potential errors.

- ***Build Features for Balancing and Monitoring:*** Developers should consider features that help both students and teachers track AI usage. This could include a usage dashboard that shows how much a student relies on the AI for a final answer versus using it for hints. This data would enable teachers and students to monitor the balance between *AI-assisted learning* and the development of *independent problem-solving skills.*

By following these suggestions, teachers can make sure that AI tools like ChatGPT improve rather than compromise the learning process, so preparing students for success in a world going more and more digital.

REFERENCES

Berger, R. (2015). Now I see it, now I don't: Researcher's position and reflexivity in qualitative

research. Qualitative Research, 15(2), 219-234. https://doi.org/10.1177/1468794112468475

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77-101. https://doi.org/10.1191/1478088706qp063oa

Chica, M., Guerra, M., & Guerra, G. (2023). The role of artificial intelligence in the development of teaching effectiveness: A tool for personalization of learning in higher education. The IAFOR Conference on Educational Research & Innovation: 2023 Official Conference Proceedings. https://doi.org/10.22492/issn.2435-1202.2023.14

Clandinin, D. J., & Connelly, F. M. (2001). Narrative inquiry: Experience and story in qualitative research. Visual Arts Research, 27(1), 107-111. https://www.jstor.org/stable/20716027

Creswell, J. W., & Poth, C. N. (2018). Qualitative inquiry and research design: Choosing among five approaches (4th ed.). Sage Publications.

International Commission on the Futures of Education. (2021). Reimagining our futures together: A new social contract for education. UNESCO. https://doi.org/10.54675/ASRB4722

Kamberelis, G., & Dimitriadis, G. (2013). Focus groups: From structured interviews to collective conversations. Routledge.

Lagon, H. M. (2023). PHET interactive simulations in learning optics towards pre-service science teachers: A phenomenological study. American Journal of Education and Technology, 2(3), 129–135. https://doi.org/10.54536/ajet.v2i3.679

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. Teachers College Record, 108(6), 1017-1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x

Piaget, J. (1954). The construction of reality in the child. Basic Books. https://doi.org/10.4324/9781315009650

Vygotsky, L. S. (1978). Mind in society: The development of higher psychological processes. Harvard University Press. https://doi.org/10.2307/j.ctvjf9vz4

Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. Learning, Media and Technology, 45(3), 223-235. https://doi.org/10.1080/17439884.2020.1798995

World Economic Forum. (2020). The future of jobs report 2020. https://www.weforum.org/reports/the-future-of-jobs-report-2020

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? International Journal of Educational Technology in Higher Education, 16(39). https://doi.org/10.1186/s41239-019-0171-0