INSTRUMENTAL GENESIS AND COGNITIVE OFFLOADING IN STUDENT-GENAI INTERACTION: A CASE STUDY IN MATHEMATICAL MODELING

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As generative AI enters mathematics education, understanding how students use these tools becomes critical. We examine instrumental genesis and cognitive offloading in student-GenAI interaction through case analysis of one eleventh-grade student solving a modelling problem, with help-seeking behaviors served as observable indicators. Analysis revealed that the student developed a learning-oriented utilization scheme within a four-stage cycle of instrumentalization and instrumentation, demonstrating low cognitive offloading: delegating computational tasks while maintaining critical authority. This framework distinguishes productive appropriation (scaffolded engagement) from problematic patterns (complete delegation), offering analytical tools for supporting productive GenAI use in mathematics learning.

INTRODUCTION

Generative AI tools have rapidly entered mathematics education, with students increasingly using ChatGPT and similar platforms for problem-solving assistance (Kasneci et al., 2023). While these tools offer unprecedented access to explanations and computational support, concerns emerge about cognitive offloading, which refers to the tendency to delegate thinking processes to external resources (Risko & Gilbert, 2016). Recent research document “metacognitive laziness” where AI use improves immediate performance but reduces knowledge retention and transfer (Fan et al., 2025). Jose (2025) also mentioned a “cognitive paradox”, where AI can enhance learning by providing scaffolding and personalized support, yet simultaneously risks eroding critical thinking when students over-rely on AI-generated solutions. However, existing studies focus primarily on learning outcomes rather than interaction processes, leaving a critical gap: we lack understanding of how students actually apply GenAI during problem-solving and what distinguishes productive from problematic use patterns.

This gap is both theoretical and practical. Without frameworks for analyzing student-GenAI interaction mechanisms, educators cannot recognize emerging usage patterns or support productive appropriation. Research examining AI in education often treats the tool as a black box, measuring inputs and outputs while ignoring the interaction processes that determine learning impacts. There is a need to reveal how students shape AI use and how AI shapes student thinking.

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We try to address this gap though instrumental genesis theory (Rabardel, 2002; Verrillon & Rabardel, 1995), which explains how artifacts become instruments through instrumentalization and instrumentation. We integrate cognitive offloading perspectives to examine the mechanisms through which different utilization patterns affect learning, using help-seeking behaviors as observable indicators. This study examines two questions:

RQ1: What instrumentalization and instrumentation process characterizes a student's interaction with GenAI during mathematical modelling?

RQ2: What utilization scheme emerges, and what cognitive offloading pattern does it exhibit?

THEORETICAL FRAMEWORK

Instrumental Genesis

We adopt Rabardel's (2002) instrumental genesis theory, which distinguishes between artifacts (neutral objects) and instruments (tools appropriated by users for specific purposes). Instrumental genesis theory has been productively applied to understanding student interactions with digital technologies in mathematics education (Trouche, 2004), demonstrating its relevance for analyzing technology-mediated learning. The transformation from artifact to instrument occurs through two bidirectional processes. Instrumentalization refers to users shaping tool functions and adapting tools to their needs, such as selecting which features to use, how to formulate queries, and when to invoke assistance. Instrumentation refers to tools shaping users' thinking and actions, such as how tool responses influence problem-solving strategies, recalibrate expectations, and structure subsequent approaches. Through repeated cycles of instrumentalization and instrumentation, users develop utilization schemes: stable patterns of tool use characterized by specific goals, interaction sequences, and use of strategies. In GenAI contexts, utilization schemes emerge as students determine what assistance to seek, how to formulate requests, and how to integrate AI responses into their problem-solving processes. Instrumental genesis has been applied to mathematics technology, for example, Artigue (2002) showing that productive tool use requires balancing technical operations with conceptual work, which is directly relevant to GenAI interaction where students need to determine which tasks should be delegated to the system and what to retain.

Cognitive Offloading in AI-Mediated Learning

Cognitive offloading describes the human tendency to use external resources to reduce internal cognitive demands (Risko & Gilbert, 2016). While offloading can be productive when it frees cognitive capacity for higher-order thinking, AI in education presents what Jose (2025) describes as a cognitive paradox: the same tools that can enhance learning through scaffolding can erode critical thinking through over-reliance. Recent research reveals problematic patterns in GenAI use. Fan et al. (2025) document "metacognitive laziness" where ChatGPT improved students' immediate problem-

solving performance but significantly reduced knowledge retention, comprehension, and transfer. However, Hong et al. (2025) demonstrate that structured cognitive offloading can enhance learning when students maintain strategic control over what to delegate and what to retain. The key distinction lies between scaffolded engagement, where external tools support reasoning, and complete delegation, where tools replace reasoning.

Analytical Framework

To operationalize utilization schemes empirically, we analyze help-seeking behaviors as observable indicators of cognitive offloading levels. Building on Newman's (2000) framework, we identify four help-seeking types reflecting different instrumentalization approaches and offloading patterns: instrumental help-seeking (explanation-seeking, low offloading), judgmental help-seeking (verification-seeking, moderate offloading), executive help-seeking (answer-seeking, high offloading), and task completion help-seeking (full delegation, highest offloading). These behavioral indicators enable identification of utilization schemes as they emerge through student-GenAI interaction, connecting observable actions to underlying cognitive processes.

METHODS

Participant and Task

This study examines one eleventh-grade female student (S1) from a high school in China. S1 consistently scored in the top 10% of her grade, had participated in mathematics competitions, and demonstrated strong logical reasoning and mathematical communication abilities. S1 had occasionally used generative AI tools prior to the study but had no systematic experience with AI-assisted mathematical problem-solving.

S1 solved a yeast population modelling problem with GenAI assistance. The task presented experimental data on yeast growth and asked students to establish a mathematical expression simulating the population growth process. The problem required identifying an appropriate growth model, determining parameters, validating fit against data, and interpreting results, which demanding both conceptual understanding and technical competence, alongside biology background knowledge that S1 lacked, where GenAI could provide some help.

Data Collection and Analysis

Data included screen recordings capturing all GenAI interactions, audio recordings of think-aloud protocols, and S1's written work. GenAI (GPT-4o) was preset with a prompt to act as a mathematics tutor providing guidance rather than direct answer. S1 was instructed to verbalize her thinking throughout the problem-solving process. Each interaction episode was coded according to two dimensions: the stage of instrumental genesis (Diagnosing, Asking, Evaluating, or Processing) and the specific action type within that stage (Table 1).

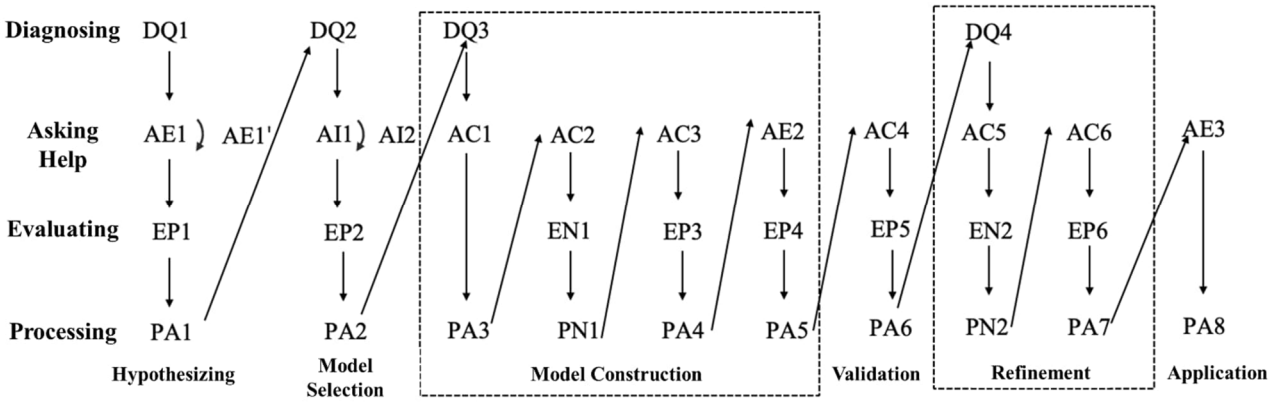
Table 1: Interaction Stage Code and Definitions

Stage	Code	Stage	Definition
Diagnosing	DQ	Diagnosing Questions	Assess and decide how to use GenAI
Asking Help	AI	Instrumental-Help	Request hints for problem-solving
	AE	Executive-Help	Request specific methods to the answer
	AJ	Judgmental-Help	Determine whether a response is correct
	AC	Completing Task-Help	Request the final answer to the problem
Evaluating	EP	Evaluating Positive	Accept or affirm the response as useful
	EN	Evaluating Negative	Identify inadequacies or errors in response
Processing	PA	Processing-Applying	Apply GenAI's output to problem-solving
	PN	Processing-Neglecting	Neglect the response and continue

RESULTS

S1's interaction with the yeast population modelling problem unfolded through four stages, which is not linear progression but multiple interconnected cycles (Figure 1), revealing both instrumentalization and instrumentation processes. We present findings in two complementary analyses: the interaction process that presents an instrumental genesis cycle and the utilization scheme that developed.

Figure 1: Interaction Process of S1



The Instrumental Genesis Cycle

S1 began by diagnosing her knowledge gap (DQ1), recognizing she lacked the biology background the problem required. She formulated two foundational questions: "What factors impact the growth of a population?" and "What kind of function model should be used to construct the expression?" These questions demonstrate purposeful instrumentalization, which targets specific conceptual gaps rather than seeking complete solutions. GenAI suggested a discrete logistic model ($\Delta p_n = k \times p_n \times (1 - p_n/N)$, where k is growth rate and N is carrying capacity). Rather than proceeding with this suggestion, S1 immediately requested elaboration: "Could you explain this model?" She sought understanding of the model's logic, key features, and mathematical structure before application.

After processing GenAI's explanation (PA1), S1 redirected the interaction. When GenAI offered further explanation, S1 declined and instead specified a computational task: "calculate Δp_n when N = 665, then graph ($p_n \times (1 - p_n/N)$, Δp_n)". This redirection demonstrates adaptive instrumentalization: S1 had developed sufficient understanding to determine next steps independently and reshaped GenAI's function from explainer to computational assistant.

The interaction revealed productive instrumentation when S1 requested: "Using $\Delta p_n = 0.54 * (p_n * (1 - p_n / 665))$ and $p_1 = 9.6$, derive the expression for p_n." GenAI responded: "The nonlinear recurrence makes closed form solutions difficult. Would you like numerical iteration instead?" This exchange shows how GenAI's mathematical expertise influenced S1's approach, where she adapted her strategy while maintaining problem-solving agency: "Calculate p_n values for n = 1, 2, …, 19."

S1's critical engagement became evident during model verification. Examining visualizations, she identified insufficient precision and requested parameter adjustments to minimize error. When her initial specification was imprecise and GenAI misunderstood, S1 revised her communication: "Adjust k and N to minimize absolute difference, with N greater than 661.8." This iterative ask-evaluate-refine sequence occurred three times, with each negative evaluation (EN4, EN5) triggering scheme adjustment. S1 was developing not only conceptual understanding but also communicative competence in using GenAI effectively, which is a sophisticated form of instrumentalization.

The interaction concluded with S1 requesting real-world interpretations: "What insights does this provide for controlling invasive species and developing economic crops?" With extensive computational support, she was able to explore higher-order connections between mathematical model and biological applications.

S1's complete interaction involved 12 asking episodes, 8 evaluations (including 2 negative), and 10 processing steps across six modeling phases (Figure 1). The pattern reveals continuous negotiation between student and tool: S1 shaped GenAI's function as her understanding deepened (instrumentalization), while GenAI's responses

structured her modeling approach and recalibrated her analytical strategies (instrumentation). When output proved inadequate, S1 revised her approach rather than accepting limitations or abandoning goals. She maintained strategic control throughout: diagnosing needs, formulating targeted questions, evaluating responses critically, and processing information selectively.

Utilization Scheme: Learning-Oriented with Scaffolded Engagement

Analysis of the questions that S1 asked reveals a learning-oriented utilization scheme characterized by scaffolded engagement, that is, exhibits low cognitive offloading where GenAI supported rather than replaced reasoning. S1 strategically delegated computational tasks while maintaining ownership of conceptual work and critical judgment.

S1 began with instrumental help-seeking: “What factors impact the growth of a population? What kind of function model should be used to construct the expression? Can you explain the discrete logistic model?” These explanation-seeking questions demonstrate low cognitive offloading. Rather than asking “How do I solve this?”, S1 requested knowledge enabling her own problem-solving. This reflects productive cognitive offloading: using external resources to build capacity rather than bypass thinking (Hong et al., 2025).

Once foundations were established, questions shifted to computational tasks: “Calculate Δp_n when N = 665 and create a graph” and “Calculate p_n for n = 1, 2, …, 19.” While these involved higher delegation, S1delegated execution while retaining strategic control – she determined what to calculate and why. The cognitive work of problem-solving direction remained hers. This selective offloading distinguishes scaffolded engagement from complete delegation.

The conceptual resonance between the beginning and end of this interaction is impressive. After computational tasks, S1 returned to higher-order instrumental help-seeking: “What insights does this provide about controlling invasive species and developing economic crops?” These questions sought real-world interpretation, transforming mathematical results into meaningful understanding. This demonstrates that S1 used GenAI to enhance, not replace, cognitive processes. High-offloading students terminate interaction once computational outputs are obtained, S1 pursued deeper interpretation.

Iterative refinement further reveals low offloading. During model optimization, S1’s initial specification was imprecise, where GenAI misunderstood. Rather than accepting results, S1 revised twice, ultimately adding constraints: “Minimize difference with N > 661.8.” This persistence demonstrates critical evaluation: judging outputs against her standards and demanding better. Each refinement required diagnosing inadequacy, reformulating requests, and evaluating results. High-offloading students accept initial outputs, while S1’s iterative approach maintained cognitive engagement.

Notably absent was judgmental help-seeking strategy. S1 never asked GenAI to verify her work. When GenAI offered to check comprehension, S1 declined and redirected. She evaluated GenAI's responses but didn't seek GenAI's evaluation of her thinking. This asymmetry indicated metacognitive control: S1 determined what she understood and needed. This contrasts with verification schemes where students frequently seek AI confirmation.

The scheme reflects successful instrumentalization: shaping GenAI as scaffold through strategic offloading decisions. S1's foundational investment enabled later strategic delegation, while complete early delegation might foreclose scheme development. The help-seeking behaviors observable in S1's questions revealed cognitive offloading patterns characteristic of productive use: using tools to extend, rather than replace, the reasoning process.

Discussion and Conclusion

This case study demonstrates that instrumental genesis theory, integrated with cognitive offloading perspectives, provides a productive framework for understanding student-GenAI interaction in mathematics problem-solving. S1's interaction revealed how utilization schemes develop through continuous negotiation between instrumentalization (student shaping tool use) and instrumentation (tool shaping student thinking), with help-seeking behaviors serving as observable indicators of underlying cognitive offloading patterns.

The learning-oriented scheme S1 developed, which is characterized by strategic delegation of computational tasks while maintaining conceptual work and critical judgement, demonstrates that productive GenAI appropriation is possible in mathematics learning. This finding contrasts with growing concerns about "metacognitive laziness" (Fan et al., 2025) and cognitive dependency in AI-assisted learning. S1's pattern of low cognitive offloading, evidenced by her understanding-seeking questions, iterative refinement, and retained evaluative authority, reveals mechanisms distinguishing productive from problematic tool use.

The instrumental genesis framework offers educators and researcher analytical tools for recognizing utilization schemes as they emerge. Rather than evaluating GenAI use as simply "good" or "bad", this framework enables identification of specific instrumentalization and instrumentation processes that characterize different schemes.

This current study's single-case design limits generalizability but provides depth necessary for understanding mechanisms. S1 represents one trajectory among multiple possible patterns. Future research could examine utilization scheme distribution across larger samples, factors influencing scheme development, and whether schemes remain stable across different mathematical domains or adapt flexibly. Longitudinal studies may investigate whether schemes formed in early stages constrain or facilitate subsequent knowledge acquisition patterns, and whether explicit guidance on effective instrumental strategies promotes scheme development.

As GenAI tools become ubiquitous in mathematics education, understanding how students use these tools becomes critical. This study reveals that the manner in which tools are employed may influence learning outcomes. S1's learning-oriented scheme demonstrates that GenAI can function as cognitive scaffold rather than cognitive substitute when students develop utilization schemes characterized by strategic offloading, maintained critical authority, and persistent conceptual engagement. The instrumental genesis lens provides both theoretical understanding and practical guidance for supporting productive GenAI appropriation in mathematics learning environments.

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