EDUMATSAINS
JURNAL PENDIDIKAN MATEMATIKA DAN SAINS
E-ISSN:2527-7235
Volume 11 Issue. 2, October 2026, pp 114-132
http://ejournal.uki.ac.id/index.php/edumatsains

Learner Agency in AI-Assisted Mathematics Learning: An Exploratory Case Study through the Lens of Three AIEd Paradigms and Mathematics Noticing

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Article Info

Article history:
Received: July 6th, 2026
Revised: October 17th, 2026
Accepted: October 21st, 2026
Available online: October 31st, 2026

https://doi.org/10.33541/edumatsains.v11i2.8516

Abstract

This research explores how a prospective mathematics teacher exercises learner agency while interacting with Generative Artificial Intelligence (GenAI) in studying injective, surjective, and bijective functions in a Real Analysis course. Using an exploratory case study design with one purposively selected participant from a broader study of ten participants, data were collected through screen recordings, presentations of understanding, and interviews during a 50-minute interaction episode. Analysis was conducted by coding participant prompts into the Three AIEd Paradigms (AI-directed, AI-supported, AI-empowered) and coding AI responses along with participant reactions into three dimensions of Mathematics Noticing (attending, interpreting, deciding). The findings revealed six patterns: efforts to establish Academic Common Ground before asking AI, critical evaluation of AI responses through multisource verification, detection of conceptual gaps in AI explanations, positioning AI as a tool for confirming independent reasoning, two instances of accepting AI explanations without further verification, and indications of conceptual understanding that Nadila was able to demonstrate during the presentation session. Behaviors associated with the AI-supported and AI-empowered configurations emerged at different moments within a single interaction session, alongside moments when critical evaluation was absent, and therefore did not support the notion of a stable developmental progression from one paradigm to another. The dimensions of attending, interpreting, and deciding were observed to operate interdependently, and the instructor was found to play a role as a reference authority source, evaluation benchmark, source of academic context, and interpretative boundary, indicating that learner agency is formed within the triad of human-AI-academic context. As a single exploratory case study, these findings provide empirical illustrations of the manifestation of learner agency in AI-assisted mathematics learning, as well as initial propositions for further research, rather than a general model of progression.

Keywords: Learner Agency; Generative AI; Three Aied Paradigms; Mathematics Noticing; Case Study

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1. Introduction

The rapid development of generative Artificial Intelligence (GenAI) has been widely utilized in higher education (Asad & Ajaz, 2024; Jogezai et al., 2026; Pang & Wei, 2025). This generative AI is also extensively used by mathematics education students (Awang et al., 2025; B. Liu et al., 2026; Sani et al., 2026). In mathematics learning, AI can help explain abstract concepts and provide quick feedback (Arya & Verma, 2024; Baidoo-Anu & Ansah, 2023; Mishra et al., 2024; Yarlagadda, 2025), but its responses do not always align with students' levels of understanding and may contain conceptual errors or hallucinations (Arya & Verma, 2024; Baidoo-Anu & Ansah, 2023; Mishra et al., 2024; Yarlagadda, 2025), which risks encouraging passive acceptance of answers without critical evaluation (Darvishi et al., 2024). Thus, the effectiveness of AI-assisted learning is determined not only by the quality of AI outputs but also by students' ability to direct and evaluate their interactions with the AI (Urooj Bashir & Raheil Rashid, 2026).

Research on generative AI in education often positions AI as a tutor, guide, critic, or reviewer that directs the learning process, or focuses on prompt engineering as a technical strategy to enhance AI output quality (Serra & Oliveira, 2025). However, how students themselves exercise agency to build contextual information, evaluate mathematical explanations from AI, identify its conceptual limitations, and decide when to use or not use AI has received limited attention. In this study, learner agency is conceptualized as the capacity of learners that encompasses four dimensions: intentionality (including goal-setting and decision-making competencies), forethought, self-regulation (ongoing evaluation and monitoring of the learning process), and self-reflectiveness (Code, 2020). One relevant behavior related to this gap is providing academic context before asking AI, which can be understood from a Human-Agent Interaction perspective as an effort to establish common ground to reduce communication failures with conversational agents (Tolzin & Janson, 2026). Previous research has examined how college students use GenAI and how prompt engineering improves the quality of AI outputs, but our understanding of how students themselves exercise agency to establish contextual information (common ground), evaluate AI explanations, and regulate their use of AI remains limited. This empirical gap is the focus of the present study.

To understand the configuration of student-AI relationships, this study employs the framework of Three AIEd Paradigms (Ouyang & Jiao, 2021): AI-directed (AI dominates the learning process), AI-supported (students and AI contribute together), and AI-empowered (students control AI as a learning partner). These three paradigms are treated as configurations of interaction that can be observed at a particular moment, rather than developmental stages that must be followed sequentially.

As a complementary lens for examining the cognitive processes underlying these three configurations, this study uses the Mathematics Noticing framework. Jacobs et al. (2010) introduced professional noticing of children’s mathematical thinking, namely the skill of recognizing and responding to students’ mathematical thinking. It consists of attending (teachers

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notice details of the strategies students use), interpreting (teachers make sense of those strategies to infer students' mathematical understanding), and deciding (teachers determine the next steps based on that understanding). In its original framework, the object of noticing is students' thinking strategies, and the subject is the teacher. This study adapts it to a different context: the object of noticing is AI responses and the mathematical processes within them, while students are positioned as the ones who read, assess, and follow up on those outputs. Operationally, attending means that students notice the details of the AI output (steps, representations, inconsistencies); interpreting means that students make mathematical sense of the AI output, such as explaining why a particular AI step is correct or incorrect; and deciding means that students determine what to do after reading and interpreting it, such as using, correcting, rejecting, or verifying the AI output against other sources. This adaptation is exploratory and has not yet been independently validated; other frameworks, such as metacognition or self-regulated learning, may explain some of the same behaviors, and this limitation is further discussed in the Methods and Conclusion sections.

Both frameworks are used together and complement each other: the Three AIEd Paradigms explain the configuration of student-AI relationships at a moment of interaction, while Mathematics Noticing explains the specific cognitive processes underlying those configurations; for example, in the AI-empowered configuration, attending is done critically, interpreting is conceptually based, and deciding is done deliberately and reasonably.

Based on the description above, this study aims to explore how a prospective mathematics teacher exercises learner agency while interacting with GenAI in learning Real Analysis, with two research questions:

1. How does a prospective mathematics teacher exercise learner agency while interacting with GenAI in learning Real Analysis?
2. How can the Three AIEd Paradigms and Mathematics Noticing framework be used to characterize that agency?

As an exploratory single case study, the findings generated are intended as empirical illustrations and initial propositions for further research, not generalizations.

2. Methods

This research employs a qualitative approach with an exploratory case study design to understand how learner agency is manifested in mathematics learning interactions assisted by Generative Artificial Intelligence (GenAI). This design was chosen because the research focuses on a single, information-rich case, allowing for an in-depth exploration of the process of student interaction with AI in learning function material in the Real Analysis course (Patton, 2015)As a single exploratory case study, the findings are intended as empirical illustrations and initial propositions for further research, rather than generalizations.

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The participant is a fourth-semester Mathematics Education student at a university in Cirebon City, referred to as Nadila, selected from ten participants in a broader study through purposeful sampling. The selection criteria included the completeness of data from three sources (screen recordings, presentations, interviews) and the variation of interaction strategies with AI, which were established after the researcher reviewed all data from the ten participants.

The interactions analyzed took place within the context of the Real Analysis course. Nadila has frequently used GenAI, including ChatGPT, Gemini, and Bing. This interaction was a task assigned by the instructor to support this research: the instructor provided documents on injective, bijective, and surjective functions and then asked students to understand them with the help of AI, without guidance from the instructor or researcher on how to use AI, allowing for authentic observation of students' natural habits and whether understanding was achieved. The duration of the interaction was 50 minutes, using the free version of ChatGPT without active browsing features; although Nadila is accustomed to using three GenAI systems, in this episode, she only utilized ChatGPT.

The unit of analysis is the learning episode on functions, which consists of a series of interactions between Nadila and AI in an effort to understand injective, bijective, and surjective functions, with case boundaries encompassing all interactions from the first prompt to the presentation and reflective interview afterward.

Participants provided written informed consent covering screen recording, presentations, and interviews. Participants' identities were anonymized using pseudonyms, and all raw data were stored securely and accessible only to the research team.

Data were collected from three sources: screen recordings documenting all AI prompts and responses during the learning session, presentations assessing students' understanding after the AI interaction session, and semi-structured interviews exploring the reasons behind each action. Screen recordings were treated as the primary evidence of the behavior that actually occurred, while interviews were used to explain the reasons behind those actions.

The data analysis process involved several stages. First, all data (screen recordings, presentations, and interviews) were collected and organized into a unified research dataset. Second, all data were read to identify segments showing how participants interacted with AI while learning mathematics. Third, coding was conducted in NVivo in two layers. The first layer coded each prompt submitted by participants into the Three AIEd Paradigms categories (AI-directed, AI-supported, and AI-empowered) to determine which paradigm was most dominant in shaping participants' interactions with AI based on the patterns of prompts they used. The second layer coded each AI response, along with the participant's reaction to it, according to the three dimensions of Mathematics Noticing (attending, interpreting, and deciding) (Jacobs et al., 2010). Fourth, the coded segments were grouped according to shared meanings to develop themes representing patterns of learner

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agency. Fifth, relationships between the empirical findings and the two theoretical frameworks were analyzed to explain how learner agency was manifested during interactions with AI.

For each theme, the evidence was organized in a traceable sequence: prompt → AI response → participant reaction → follow-up prompt (if any) → interview explanation → code → theoretical interpretation. A chronological interaction map was also created to show when each behavioral pattern emerged during the 50-minute period, in order to examine whether the emergence of the themes followed a particular sequence or occurred in alternation.

Mapping episodes to the dimensions of Mathematics Noticing takes potential multiple interpretations into account. For instance, providing academic context before asking AI may be read as deciding or as metacognitive planning; in this study, it is coded as deciding because the focus of the analysis is on the action of explicitly determining the direction of interaction with AI through prompts, rather than on the internal cognitive processes of the participants.

The credibility of the findings is reinforced through triangulation of three data sources and pattern matching between empirical patterns and conceptual patterns of both frameworks. The analysis is conducted iteratively to maintain consistency of meaning across sources. Thick descriptions are presented so that readers can assess the potential transferability of the findings to other contexts, rather than to guarantee their transferability. Confirmability is sought through the researcher's reflective notes (reflexive memos) throughout the analysis process, discussions with the supervising lecturer as a form of peer debriefing, and tracing the decision-making process of coding (audit trail) from initial codes to final themes. As the sole researcher situated in the same program of study as the participant, this position is acknowledged to facilitate the interpretation of the participant's academic context (common ground), while also potentially influencing the interpretation of behaviors categorized as forms of agency.

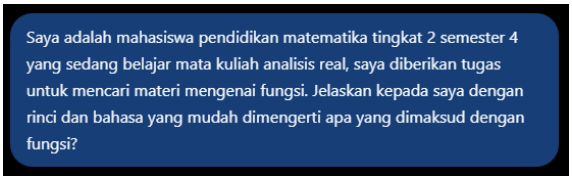
3. Result and Discussion

3.1 Building Academic Common Ground Before Interacting with AI

The analysis of the screen recording and presentation shows that Nadila did not immediately ask the AI a mathematical question. Instead, she first provided her academic context through the following prompt:

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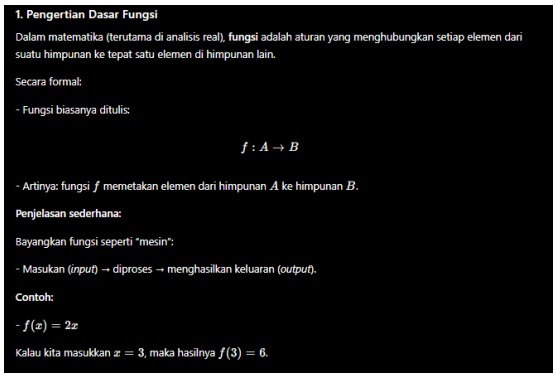
Figure 1
Screen Record, Nadila



Translate: "I am a fourth-semester Mathematics Education student, currently studying Real Analysis, and I already understand basic function concepts from my first year. Now, please explain surjective functions at a level appropriate for my college stage."

In response, the AI provided an explanation using the formal definition of a function in accordance with the standards of the Real Analysis course, rather than the informal definition commonly taught at the secondary-school level or in courses she had previously taken. Nadila expressed satisfaction with the response because it met her expectations and immediately continued the interaction by asking about injective functions.

Figure 2
Output AI



During the presentation and interview, Nadila explained why she initially gave the AI a prompt like that, which reinforces this finding:

> *"I gave an introduction at the beginning; I explained that I'm a mathematics education major. To make it more specific for the details, because I've already learned about functions in high school, so AI can tell the difference."* [Presentation, Nadila]

> *"Then there's the fourth semester of the second year, because in the first year I also learned about functions in another lecture. So there's a clear distinction."* [Presentation, Nadila]

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These statements show that she provided information about her program of study, semester, and existing knowledge, which she intentionally conveyed at the beginning of the interaction so that the AI would distinguish between the formal definition relevant to the course Nadila was currently taking.

This reflects an effort to build common ground from the perspective of Human-Agent Interaction. Common ground itself is the way humans build a shared understanding with conversational agents to make communication more effective and reduce failures during (Clark, 1996; Tolzin & Janson, 2026). To establish this common ground, it is necessary to provide a knowledge base at the beginning of the interaction. This is demonstrated by Nadila's practice of expressing her academic background first before asking questions to AI. Thus, in this specific case, there is an indication that disclosing academic background affects the form of the AI's response, although this simplicity is still limited to one episode of interaction and cannot be generalized as a common ground mechanism that applies to every AI interaction in general.

Within the framework of the Three AIEd Paradigms, her disclosure of academic background demonstrates characteristics of the AI-supported paradigm. According to Ouyang and Jiao (2021), the main feature of this paradigm is that learners act as collaborators in building knowledge with AI, where AI will provide output that is more aligned with what learners want. In the context of Mathematics Noticing, this behavior represents the deciding dimension, as Nadila determines the direction of the interaction before AI provides output (Jacobs et al., 2010). This categorization can also be interpreted as a form of metacognitive planning.

These findings also extend previous research that prompt engineering is a technical strategy to improve the quality of AI output (Lee & Palmer, 2025). This study also shows that conveying academic context helps enhance the quality of AI output and represents an early stage in the development of learner agency from collaboration toward full student leadership over their learning process. The choice of the deciding category here is based on the focus of the analysis on the explicit actions that guide the interaction with AI through prompts, rather than on the underlying internal cognitive processes.

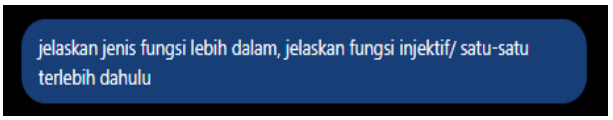
From the perspective of learner agency, this action reflects the dimension of intentionality, which is the learner's capacity to plan and pursue meaningful goals through goal-setting and decision-making competencies (Code, 2020). However, this single action does not yet demonstrate dimensions of agency that involve ongoing monitoring or evaluation, which only become apparent in subsequent themes.

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3.2 Critically Evaluating AI Responses Through Multi-Source Verification

In the next stage, Nadila submitted the same prompt to several GenAI systems (ChatGPT, Gemini, and Bing):

Figure 3
Screen Record, Nadila



The three systems provided responses with different levels of depth and focus. ChatGPT offered the most comprehensive explanation, covering the definition, examples and non-examples of injective functions, methods for checking whether a function is injective, the relationship to inverse functions, and illustrative graphs. Gemini provided a definition, ways to prove that a function is injective, and examples of injective and non-injective functions. Bing provided a definition, examples of injective functions, ways to check whether a function is injective, and several other relevant functions for comparison.

Figure 4
Output ChatGPT

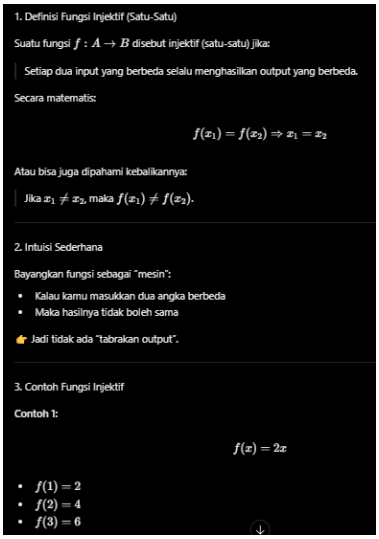
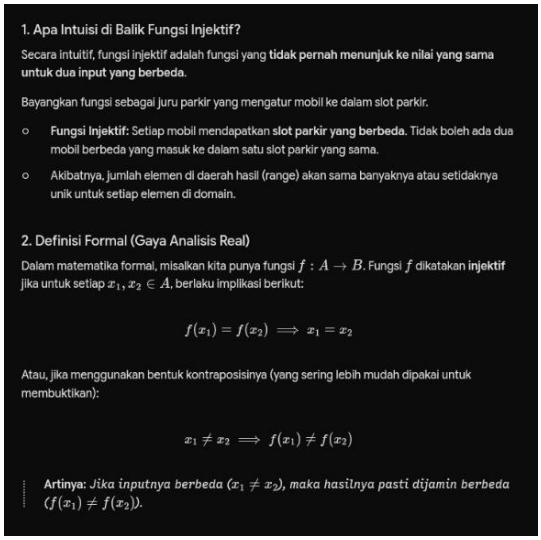
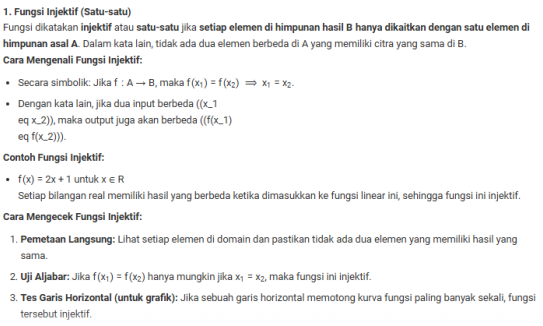


Figure 5
Output Gemini



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Figure 6
Output Bing



1. Fungsi Injektif (Satu-satu)
Fungsi dikatakan **injektif** atau **satu-satu** jika **setiap elemen di himpunan hasil B hanya dikaitkan dengan satu elemen di himpunan asal A**. Dalam kata lain, tidak ada dua elemen berbeda di A yang memiliki citra yang sama di B.
Cara Mengenali Fungsi Injektif:

- Secara simbolik: Jika $f : A \to B$, maka $f(x_1) = f(x_2) \implies x_1 = x_2$.
- Dengan kata lain, jika dua input berbeda ((x_1 eq x_2)), maka output juga akan berbeda ((f(x_1) eq f(x_2))).

Contoh Fungsi Injektif:

- $f(x) = 2x + 1$ untuk $x \in R$
  Setiap bilangan real memiliki hasil yang berbeda ketika dimasukkan ke fungsi linear ini, sehingga fungsi ini injektif.

Cara Mengecek Fungsi Injektif:

1. **Pemetaan Langsung:** Lihat setiap elemen di domain dan pastikan tidak ada dua elemen yang memiliki hasil yang sama.
2. **Uji Aljabar:** Jika $f(x_1) = f(x_2)$ hanya mungkin jika $x_1 = x_2$, maka fungsi ini injektif.
3. **Tes Garis Horizontal (untuk grafik):** Jika sebuah garis horizontal memotong kurva fungsi paling banyak sekali, fungsi tersebut injektif.

Nadila compared the three GenAI outputs and reread them before continuing with a follow-up prompt in ChatGPT:

Figure 7
Screen Record, Nadila



The explanation in the interview reinforces this pattern:

> *"Yes, I can use two or three AIs... I look at everything first, which one connects best, which is most similar to how the lecturer explains it."* [Interview, Nadila]

This statement shows that Nadila did not regard AI as her sole source of truth. She may have had doubts about immediately accepting AI-generated outputs, so she needed several sources of information to evaluate critically, while the professor's explanation remained the primary reference for assessing the relevance and accuracy of the AI responses.

This behavior shows that Nadila has moved beyond merely collaborating with AI to construct knowledge and has also begun to take control of constructing her own understanding of knowledge. This is a key characteristic of the AI-empowered paradigm. According to Ouyang & Jiao (2021), a primary feature of the AI-empowered paradigm is that learners have full agency in making decisions related to their learning process. In Nadila's case, AI acts as one of the comparative sources under the evaluative control of the student, no longer just as a collaborator. In the framework of Mathematics Noticing, Nadila's behavior of comparing and validating outputs from various AIs represents the interpreting dimension, which is the capacity to make sense of the truth

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and appropriateness of mathematical information from various sources before use (Jacobs et al., 2010).

These findings align with various studies emphasizing the importance of the ability to systematically verify as an indicator of the critical evaluation stage in AI literacy. This ability distinguishes users who merely recognize the limitations of AI (basic verification) from those who actively assess the appropriateness of AI outputs within specific academic disciplines (J. P. Liu & Levy, 2026; Papaneophytou & Nicolaou, 2025).

These findings open up important discussions about the role of lecturers in participants' interactions with AI. From the interview excerpt above, it is clear that the lecturer's explanation serves as the primary reference for Nadila in assessing which AI response is most appropriate to follow. The lecturer was used by Nadila as a source of authoritative reference because their way of explaining served as the standard of truth against which comparisons were made; as an evaluative benchmark because it was used to assess the correspondence between the AI's responses and the course material; as a source of academic context because it provided a reference for the expected level of depth and style of explanation; and as a boundary for interpretation because AI responses considered less consistent with the lecturer's explanatory style tended not to be selected or were only partially incorporated. These findings show that, in this case, AI did not function independently but operated within a human-AI-academic context triad, with the lecturer serving as the link connecting participants' evaluations of AI output with the academic standards applied in their class.

From the perspective of learner agency, this pattern reflects the dimension of self-regulation, which involves ongoing reflection and evaluation of progress throughout the learning process (Code, 2020). The finding that the lecturer became the primary reference point in this evaluation process is also consistent with the sociocultural view that learner agency does not exist solely at the individual level but is mediated through interaction with more experienced individuals within learners' educational contexts (Vygotsky, 1978). This pattern also aligns with the finding that students' agency in interactions with AI varies considerably and cannot automatically be assumed to be uniform (O'Dea et al., 2026).

3.3 Identifying Conceptual Gaps Through Interaction with AI

Analysis of the screen recordings showed that Nadila read the explanations provided by AI carefully. She also paid attention to details that AI had not explained sufficiently, as reflected in the following prompt:

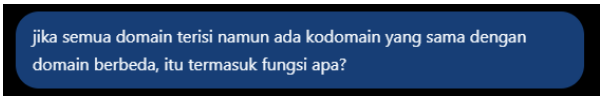
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Figure 8
Screen record, Nadila



When AI explained the concepts of injective, surjective, and bijective functions, Nadila realized that the explanation did not address the condition when multiple elements from the domain are mapped to the same codomain element. This conceptual gap prompted her to ask follow-up questions:

Figure 9
Screen Record, Nadila



In the interview, she also expressed her reasons for asking that question to AI:

> *"Because from what I read before, it was just like if the domain had to be filled one-to-one into the codomain. Then, like, what about that, it wasn't explained like that. Like if the domains are different but the codomain is the same, where does it actually go? Well, that wasn't explained in the AI, so I asked on my own."* [Interview, Nadila]

The two pieces of data above show that the follow-up questions arose not because the AI provided incorrect answers, but because Nadila paid close attention to every detail of the explanations provided by the AI, allowing her to identify areas where the AI's explanations lacked sufficient detail.

This pattern shows that Nadila did not merely read and passively accept the AI's explanations; instead, she actively evaluated the completeness of the explanations she received. In Mathematics Noticing, recognizing such gaps is coded as attending, referring to the ability to notice relevant mathematical details, including those left unexplained by the AI (Jacobs et al., 2010). The specific questions Nadila asked to address these shortcomings demonstrate the connection between attending and deciding: recognizing a gap directly prompted her to seek further explanation in order to achieve a more complete understanding. Within the Three AIEd Paradigms, this behavior reflects the characteristics of an AI-empowered configuration, because Nadila treated the completeness of the AI's explanations as something to be examined and questioned rather than simply accepted (Ouyang & Jiao, 2021).

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This concept also illustrates the aspect of foresight in Bandura's theory of agency, highlighting the ability to foresee the necessity for further comprehension prior to taking action (Code, 2020). Metacognitive awareness of one's limitations in understanding implies that agency in this context is not simply reactive but entails intentional foresight and subsequent reflection.

The research suggests that AI can promote conceptual exploration and enhance mathematical comprehension when students engage with AI in a critical manner, instead of a passive one (Canonigo, 2024; Kim et al., 2026; Shahzad et al., 2025). Thus, Nadila's interaction with AI does not diminish mathematical thinking activity, but rather shows that learner agency allows students to leverage AI's limitations as opportunities to build a more comprehensive conceptual understanding.

3.4 AI as a Confirmation Tool in Learning Mathematics

At this stage, Nadila requests practice questions from AI through a prompt:

Figure 10
Screen Record, Nadila



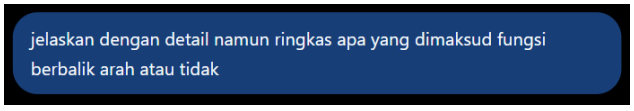
From the four questions provided, she responds:

Figure 11
Screen Record, Nadila



The AI then corrected that answer and provided an explanation of the process. Nadila paid attention to the explanation of the correction and accepted it; however, she then questioned a term that appeared in the AI's explanation regarding whether a function "reverses direction or not," through a follow-up prompt:

Figure 12
Screen Record, Nadila



he three prompts above show that Nadila first tried to request problems involving injective, surjective, and bijective functions. She then answered them independently before asking the AI to

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provide corrections, rather than asking it to help her solve the problems. Even when receiving corrections from the AI, she continued to question aspects of the explanation that she did not yet fully understand, instead of accepting the entire explanation without further clarification.

In the interview, Nadila revealed that she did not use AI as her primary tool for solving mathematical problems. Instead, she first tried to understand a concept or problem independently before using AI to verify the understanding she had already developed. This is reflected in the following statement:

> *"I usually try first; I definitely try it myself first. If I already have the answer but I'm still unsure, then I go to AI to make sure whether my answer is correct or not."* [Interview, Nadila]

Her statement shows that AI was positioned as a tool for confirming the results of her own thinking, rather than as a tool that provides answers. Nadila's habit indicates that the learning process remained student-centered, with AI used only after the student had developed an initial understanding and identified details that still seemed uncertain. Therefore, the primary function of AI in this context was to confirm whether the answer she had obtained independently was correct, allowing AI to serve as a means of reflection and supportive validation rather than replacing the student's reasoning process (Bastian et al., 2025).

In Mathematics Noticing, this pattern demonstrates a relationship between interpreting and deciding: Nadila understood the corrective output provided by the AI and then decided to ask for further explanation of one part that she felt she had not yet fully understood, rather than immediately assuming that she had mastered the concept. In the Three AIEd Paradigms, this pattern reflects an AI-empowered paradigm configuration in which the AI was placed under Nadila's intellectual direction throughout the interaction analyzed, though not "entirely" under her control, because control over her overall learning process was not measured directly (Ouyang & Jiao, 2021).

From the perspective of learner agency, the pattern of using AI as a checker after independent reasoning aligns with the dimension of self-reflectiveness in Bandura's agency theory, which is the capacity to evaluate one's own thought outcomes before accepting them as valid information (Code, 2020). Nadila does not treat AI as her first source of answers, but rather as a checker of her own thought process. When receiving corrections, she also does not immediately consider the explanation complete, but questions parts that she does not fully understand, demonstrating that the acceptance of AI's output here is still accompanied by evaluation, rather than automatic compliance with AI's authority.

These findings reinforce previous findings that the effectiveness of using AI in mathematics learning is not determined by how often students use AI, but by how AI is positioned within the overall learning process (Gqoli & Baidoo, 2025; Infante et al., 2025). Unlike other findings that

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use AI as a provider of instant answers, Nadila's case shows that AI can function as a tool for reflection and validation when students retain control over their own thinking processes (Grinshkun & Dreytser, 2023; Neshaei et al., 2025). In this way, AI does not replace mathematical reasoning activities; rather, it supports students in reflecting on, verifying, and consolidating their understanding more critically.

3.5 Negative Cases: Moments of Absence of Verification

In addition to the four patterns above, the analysis also actively searched for moments when Nadila did not demonstrate evaluative behavior toward AI output. Two such moments were identified: at 37:05, Nadila accepted the AI's explanation of surjective (onto) functions without further verification; and at 42:29, she likewise accepted the AI's explanation of bijective functions without further verification.

These two moments differ from the patterns in Sections 3.1 - 3.4 and show that the agency observed in the earlier sections was not consistent throughout the interaction but instead emerged situationally around particular topics or moments. In the discussion of injective functions (3.2 - 3.4), Nadila consistently demonstrated behaviors of comparing, questioning, and verifying; whereas in the discussion of surjective and bijective functions, she accepted the AI's explanations without similar scrutiny. This finding indicates that behaviors associated with AI-supported and AI-empowered configurations do not necessarily remain consistent throughout a learning session. Rather, they emerge alongside moments of absent critical evaluation, depending on the learner's understanding of the material or the particular stage of the interaction.

These two moments emphasize that learner agency cannot be regarded as a fixed trait inherent in an individual but rather as something situated contextually, temporally, and intrapersonally. This agency can be highly pronounced with one topic and may not emerge with another topic within the same learning episode (Mercer, 2012). In other words, the agency observed in Sections 3.1 - 3.4 does not automatically become a permanent characteristic of the participant; instead, it emerges episodically, depending on the specific conditions of the interactional moment.

3.6 Indications of Conceptual Understanding After Interaction

As stated previously, this study primarily focuses on the participants' interaction patterns and agency with respect to AI, rather than formally measuring their mathematical learning outcomes. Nevertheless, the way Nadila presented her understanding after the interaction session indicates that she was able to articulate her own understanding accurately, as reflected in the following excerpt:

> *"Bijective means if the codomain is full and mapped one-to-one, that is called bijective."* [Interview, Nadila]

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This response shows that Nadila was able to accurately restate the definition of a bijective function in her own words, namely by relating the condition that the codomain is completely mapped (surjective) to one-to-one mapping (injective) occurring simultaneously. This indication provides an initial foundation that interaction with AI in this episode not only produces patterns of agency but is also accompanied by conceptual understanding that can be articulated independently. However, these findings remain indicative and limited to a single moment of presentation; this study does not conduct formal measurements of understanding (such as through pre- and post-interaction tests), thus claims regarding overall improvement in mathematical understanding or reinforcement of mathematical reasoning cannot be drawn from this data and require separate measurements in further research.

3.7 Learner Agency in AI-Assisted Mathematics Learning

The six findings above indicate that behaviors associated with AI-supported and AI-empowered configurations emerged at different moments within a 50-minute episode of interaction and were not uniformly applicable throughout the session. Table 1 summarizes the observed themes, configurations, and dimensions of noticing, along with estimated times of their occurrence.

Table 1.
Patterns of Learner Agency Observed in AI-Assisted Mathematics Learning

Theme	AIEd Configuration	Noticing Dimension	Time Description
Building contextual information	AI-supported	Deciding	Beginning of interaction
Critical evaluation of multiple sources	AI-empowered	Interpreting	Menit 06.15
Detecting conceptual gaps	AI-empowered	Attending → Deciding	Menit 46.07
AI as a confirmation tool	AI-empowered	Interpreting → Deciding	Menit 26.50
Negative case (surjective function)	AI-directed/ passive	-	Menit 37.05
Negative case (bijective function)	AI-directed/ passive	-	Menit 42.29

The sequence of appearances in Table 1 shows that AI-empowered-related behaviors (3.2–3.4) emerged in the middle of the session, framed by deciding behavior at the beginning (3.1) and two moments of absent verification toward the end of the session (3.5). This pattern represents an interactional configuration that shifted depending on the material being discussed: for injective functions, Nadila consistently demonstrated comparing, questioning, and verifying behaviors, whereas for surjective and bijective functions, the AI's explanations were accepted without similar examination. This difference indicates that learner agency is situational, possibly influenced by the student's level of understanding of each topic, rather than resulting from a cumulative development of ability within a single session.

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Thus, Nadila's data demonstrate AI-supported and AI-empowered configurations of behavior during the interaction, accompanied by moments in which critical evaluation was absent for certain topics. She demonstrated more observable control over the use of AI in the interaction analyzed, rather than full control over her learning process as a whole. The dimensions of attending, interpreting, and deciding were observed to function interrelatedly, preceding and following one another within the same episode rather than progressing through a fixed hierarchy.

This pattern is consistent with the view that learner agency develops through the dynamic interaction of various components within a context, rather than as a single capacity that remains stable across time and topics (Mercer, 2012). The differences in behavior between the material on injective functions and that on surjective and bijective functions reinforce this view, showing that agency is specific to particular contexts and subject matter, rather than a general characteristic possessed by learners as a whole.

The findings regarding the lecturer's role as a source of authoritative reference, an evaluative benchmark, a source of academic context, and a constraint on interpretation show that Nadila's agency toward AI does not operate independently. Instead, it is mediated through her relationship with a more experienced figure in her academic context, consistent with the principle that higher mental functions develop through mediated social processes (Vygotsky, 1978).

The indication of conceptual understanding, evident in Nadila's ability to accurately express the definition of a bijective function in her own words, provides an initial basis for suggesting that the observed pattern of agency aligns with demonstrable understanding. However, because mathematical understanding was not formally measured, this claim remains indicative and cannot be generalized as evidence of a comprehensive strengthening of mathematical reasoning.

4. Conclusion

This case study explored how a preservice mathematics teacher exercised learner agency while interacting with GenAI to learn about injective, surjective, and bijective functions in a Real Analysis course. Six findings were observed during the 50-minute interaction episode: an effort to establish Academic Common Ground at the beginning of the interaction, critical evaluation of AI responses through multisource verification, detection of conceptual gaps in the AI's explanations, positioning AI as a tool for confirming independent reasoning, two moments in which verification was absent for the surjective and bijective function materials, and an indication of conceptual understanding that Nadila was able to articulate during the presentation session.

Behaviors associated with the AI-supported and AI-empowered configurations emerged at different moments within a single interaction session, alongside moments in which critical evaluation was absent. Therefore, the findings do not support the notion of a stable developmental

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progression from one paradigm to the other. The dimensions of attending, interpreting, and deciding were observed to operate interrelatedly throughout the interaction, addressing the research question at an illustrative level. The lecturer was found to serve as a source of authoritative reference, an evaluative benchmark, a source of academic context, and a constraint on interpretation, indicating that learner agency toward AI is formed within a human-AI-academic context triad, rather than solely within a student–AI dyadic relationship.

The limitations of this study include: one participant selected purposively based on data richness, with recognized selection bias potential; one 50-minute interaction episode limiting the opportunities for additional negative case emergence; partial reliance on participant self-reports to explain the reasons behind recorded actions; adaptation of the Mathematics Noticing framework from the context of teacher noticing of children's thinking to the context of student noticing of AI outputs, which is exploratory and has not been independently validated; and the absence of formal measurement of mathematical understanding, so indications of understanding in 3.6 cannot be generalized as evidence of strengthening mathematical reasoning.

Future research should involve more participants and interaction episodes to test whether the situational patterns found here are consistent in other contexts, measure mathematical understanding separately from interaction patterns (for example, through pre- and post-interaction tests), and further examine the role of the instructor in the identified triad of human-AI-academic context in this study.

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