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Analyzing Teacher-Student Dialogues in Online One-on-One Primary Mathematics Tutoring: A Lag Sequential Analysis of Group Differences

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Abstract: This study aimed to identify effective teacher-student dialogues in online one-on-one tutoring sessions for primary mathematics. A total of 35 online videos of one-on-one tutoring sessions focused on the topic of fractions were collected and transcribed into textual data. Two key methods were employed to analyze the data. First, a hybrid coding scheme combining the Initiation-Response-Feedback (IRF) model with scaffolding techniques was used to code teacher-student dialogues from each tutoring session to categorize the session into one of two groups: the more effective tutoring and the less effective tutoring group, based on the presence of indicators suggested by the literature. Second, lag sequential analysis (LSA) was applied to compare dialogue patterns between the more and less effective tutoring groups at a more fine-grained level. Our results indicate that tutors who employed a variety of strategies, including modeling and diverse scaffolding techniques, were more effective in engaging students and addressing their learning needs. This study suggests that adaptive tutoring strategies are crucial for enhancing student understanding in primary mathematics. Future research could further refine these approaches with inputs from human experts and explore their application in different educational contexts, such as developing AI-powered chatbots capable of providing adaptive scaffolding to students beyond the classroom.

Keywords: One-on-one tutoring, teacher-student dialogues, primary mathematics, lag sequential analysis

1. Introduction

The rapid advancement of artificial intelligence (AI) has resulted in the creation of highly sophisticated large language models (LLMs). These models, typically built on deep learning and neural network architectures, are trained on extensive textual data to analyze, understand, and generate human-like language based on learned patterns (Ray, 2023). AI-powered chatbots, which are software applications designed to simulate human conversation, have become increasingly capable of understanding, interpreting, and producing human language, thereby enabling meaningful interactions with users. Their use has grown significantly in recent years, especially as instructional aids in educational environments (Zhang et al., 2023). However, despite their training on large datasets—which may contain biases or low-quality information—AI-powered chatbots do not consistently demonstrate expertise across all areas, particularly in specialized tasks (e.g. one-on-one online tutoring) (Ray, 2023).

In light of these challenges, this study aimed to compile a dataset of one-on-one online tutoring sessions focused on the topic of fractions in primary mathematics. The data collected was then annotated to identify differences in the teacher-student dialogue patterns between more and less effective tutoring groups. To guide this investigation, the following research question was posed: how do the dialogue patterns between teachers and students differ in more and less effective one-on-one tutoring sessions focused on fractions in primary mathematics? The findings from this study could shed light on the design of AI-powered chatbots equipped with effective one-on-one tutoring strategies, ultimately supporting personalized learning experiences.

2. Related Work

2.1 One-On-One Tutoring

One-on-one tutoring has long been regarded as one of the most effective methods of instruction (Bloom, 1984; Graesser et al., 2011; Zhang et al., 2021). A primary benefit of this approach is its adaptability to meet the specific learning needs of individual students, which can potentially enhance their engagement and academic performance (Siler & VanLehn, 2015). One-to-one tutoring can be structured in either a tutor-centered or a tutee-centered format. In tutor-centered sessions, the tutor designs a detailed plan based on the tutee's competencies and leads the instruction. Conversely, tutee-centered sessions are driven by the tutee's questions, with the tutor responding on-the-fly to address specific issues raised by the tutee (Zhang et al., 2021).

One-on-one tutoring is also available in both online synchronous and face-to-face modes. The online mode is increasingly popular due to its cost-effectiveness, which facilitates connections between tutors and tutees who are geographically separated (Zhang et al., 2021). Although one-on-one tutoring offers significant potential benefits, its effectiveness in boosting student engagement and achievement hinges on the quality of the tutoring provided (Cukurova et al., 2022). Effective tutoring requires appropriate scaffolding, tailored to the student's level of understanding, which encompasses strategies such as providing targeted questions, examples, hints, and explanations. It can help bridge knowledge gaps for individual students and promote independent learning by gradually reducing support as students develop skills and confidence (Wittwer et al., 2010).

2.2 Analysis of Teacher-Student Dialogues

Previous research has explored the dialogue patterns between the teacher and students during the teaching and learning process (Mercer & Dawes, 2014). The most common, minimal unit identified from these dialogues is a three-move cycle, namely the initiation-response-feedback (IRF) exchange (Sinclair & Coulthard, 1975). The initiation (I) move typically involves the teacher starting a dialogue by asking a question or prompting an action to encourage student participation in a learning process. This effort is aimed at actively engaging students in ongoing dialogue. The second move, response (R), occurs when students react to the teacher's initial dialogue. This move involves students engaging with the teacher's stimuli, effectively participating in the learning dialogue initiated by the teacher. The final move, feedback (F), completes the dialogue cycle by providing students with evaluations or corrections of their responses (Hellermann, 2003).

In its strictest form, the IRF cycle features a fixed sequence: the teacher poses a question, a student responds, and the teacher provides evaluative feedback. However, a broader understanding recognizes the IRF structure as more flexible, encompassing not only the basic moves of initiation, response, and feedback but also extended sequences (Walsh, 2011) or repetitions of certain move (Hellermann, 2003) within the IRF cycle to stimulate deeper student thinking. Moreover, the sequences of the IRF cycle can be utilized as a pedagogical tool to sustain students with learning difficulties. For instance, Molinari et al. (2013)

recognized sequences of the IRF cycle that serve different pedagogical functions, such as the scaffolding sequence (focused question, incorrect answer, scaffold by giving hints).

2.3 Indicators of Effective Tutoring

Effective tutoring has been shown to correlate with various indicators of student learning. One such indicator is the presence of active and constructive student engagement, as outlined by the Interactive Constructive Active Passive (ICAP) framework (Chi & Wylie, 2014). According to this framework, student engagement during tutoring sessions is classified as active when students undertake tasks involving some form of manipulation, such as solving problems with the guidance of the tutor. More importantly, engagement is considered constructive when students produce some sort of external outputs, such as generating deep, reasoned questions or providing self-explanations (Zhang et al., 2021).

Another potential indicator of effective tutoring involves the sequential behavior patterns of tutors. Cukurova et al. (2022) identified seven potential signifiers of effective tutor behaviors and analyzed the sequences of behaviors that occurred more frequently in effective online tutoring sessions for primary mathematics. Their findings indicate that a specific behavioral pattern—characterized by appropriate pauses after questions, followed by the initiation of students' self-corrections—can distinguish more effective tutors from less effective counterparts. The study underscores the importance of tutors asking questions, allowing sufficient time for students to respond, as well as encouraging students to recognize and correct their own mistakes.

2.4 Lag Sequential Analysis

Lag Sequential Analysis (LSA) is a method used to identify patterns within sequences of coded categories that characterize interactions, as originally described by Bakeman and Gottman (1997). It is commonly applied in behavioral and educational research to examine how one behavior or event follows another in a sequence. The process involves analyzing a frequency matrix that tracks how often specific behavioral transitions occur, calculating conditional probabilities and expected values for these transitions, and determining whether these patterns are statistically significant (Bakeman & Gottman, 1997). In simpler terms, LSA helps researchers see if certain behaviors or actions tend to follow each other more often than would be expected by chance. For instance, in a classroom setting, LSA could be used to determine if a student's asking a question is more likely to be followed by a teacher's explanation than by a student's off-task behavior.

LSA is particularly valuable in educational research because it allows for the exploration of the dynamics of teacher-student interactions and other dialogues. For example, Sun et al. (2021) used LSA to investigate the behaviors of primary school students while playing educational mobile games, comparing how these patterns differed between higher and lower-performing students. Similarly, a recent study by Ma et al. (2024) applied LSA to analyze activities in smart classrooms by encoding prize-winning teaching videos. The goal was to identify key sequences of activities and major interaction patterns between teachers and students, providing deeper insights into effective teaching strategies.

3. Method

3.1 Study Context

This study is part of a collaborative, university-funded initiative titled "Promoting Personalized Learning in Elementary Mathematics through Collaboration between Teachers and Chatbots". It was conducted during the second semester of the 2023-24 academic year at universities in Hong Kong and Shanghai. Tutee-centered tutoring was employed in this study due to its greater flexibility compared to tutor-centered tutoring, particularly in terms of session length and learning objectives. The primary objectives of this study were threefold: (1) to collect a dataset of one-on-one, tutee-centered online tutoring sessions focused on the topic of fractions in primary mathematics; (2) to code teacher-student dialogues using a hybrid scheme based on the IRF model and scaffolding techniques; and (3) to explore differences in dialogue patterns between more and less effective tutoring groups using LSA.

3.2 Participants

Participants in this study comprised 27 fifth-grade primary students, who acted as tutees, and 14 pre-service teachers majoring in mathematics education, who served as tutors during online tutoring sessions focused on the topic of fractions. All participants were Chinese and communicated in Putonghua throughout the sessions. Prior to the commencement of the study, all participants provided informed consent, indicating their willingness to participate. The participants were briefed on the study's objectives, procedures, and the nature of their involvement. They were also informed about their right to withdraw from the study at any time without any consequences. Ethical approval for the study was obtained from the university's human research ethics committee, ensuring full compliance with ethical standards for research involving human subjects.

3.3 Data Collection

Prior to the online tutoring sessions, tutees were provided with a set of mathematics questions in Chinese about fractions to attempt on their own. Table 1 shows sample questions translated into English. These questions functioned as a diagnostic tool to identify areas where students required additional support. After completing this initial task, students participated in scheduled online tutoring sessions with pre-assigned tutors to seek guidance on the problems they found challenging or were unable to solve independently. On the other hand, tutors were briefed on effective tutoring strategies before the commencement of the tutoring sessions to ensure they were well-prepared to assist their tutees. During the sessions, tutors guided the students through problem-solving processes, helping them to understand and overcome the difficulties they encountered.

As a result, a total of 35 online videos of one-on-one tutoring sessions focused on the topic of fractions in primary mathematics were collected using the online meeting platform called 'Tencent Meeting'. These videos captured teacher-student dialogues, with the duration of the sessions ranging from approximately 5 to 77 minutes. The online meeting platform automatically transcribed all video recordings into text files, which were then manually reviewed and corrected to rectify any transcription errors. This data cleansing process was essential to ensure the accuracy of the transcripts for subsequent coding and analysis.

Table 1. *List of Sample Mathematics Questions about Fractions Translated into English.*

Question Code	Question
0417-gp2	A fraction is simplified to $\frac{5}{12}$. It is known that the sum of the original numerator and denominator is 51. What is the original fraction?
0422-gp2	Compare the magnitudes of the following fractions: $\frac{3}{8}$ and $\frac{3}{11}$; $\frac{5}{6}$ and $\frac{5}{8}$; $\frac{12}{17}$ and $\frac{12}{19}$; $\frac{19}{94}$ and $\frac{19}{73}$.
0507-gp5	Dian Dian bought a book called "*Mathematics in Daily Life*". On the first day, she read $\frac{2}{9}$ of the book, and on the second day, she read $\frac{1}{6}$ of the book. What fraction of the book did she read in total over the two days?

0513-gp1	If the denominator of a fraction remains unchanged and the numerator is multiplied by 3, how does the value of the fraction change? What happens if the numerator remains unchanged and the denominator is divided by 5?

3.4 Coding Scheme

A hybrid scheme combining the IRF model with scaffolding techniques was developed to analyze the teacher-student dialogues in our dataset. Common scaffolding techniques (Van de Pol et al., 2010), including questioning, providing hints, modelling, feedback, instructing, and explaining, were integrated into the IRF model to allow for a more fine-grained categorization of each turn taken by the student or teacher during their dialogues. The detailed coding scheme used for this analysis is presented in Table 2.

The coding process was conducted independently by two researchers from the project team. Each researcher applied the coding scheme to the data, annotating the text files from the online one-on-one tutoring sessions with sequences of codes. After completing the initial coding, the two sets of codes—each labeled by a different researcher—were compared, and slight discrepancies were identified. To assess the reliability of the coding process, Cohen's kappa inter-coder reliability score was calculated, yielding a score of 86%. This score indicates nearly perfect agreement between the coders, according to the standard set by Landis and Koch (1977). The discrepancies identified were then discussed, and the coding criteria were refined to reach a consensus, thereby ensuring consistency in the final coding results.

Table 2. *Coding Scheme for Teacher-Student Dialogues.*

Code	Name	Description	Example
I-Q	Initiation: Questioning	It involves prompting students with questions that require both linguistic and cognitive engagement.	*"Can you calculate 1/2 plus 1/4? Tell me your calculation process."*
I-H	Initiation: Providing Hints	It involves providing clues or suggestions to assist the student in progressing through a problem. In such cases, the teacher intentionally refrains from offering the complete solution of detailed instructions.	*"If you have 1/2 of a pizza and I give you another 1/4, how much pizza do you have in total? Remember, when adding fractions, it is important to have the same denominator."*
I-M	Initiation: Modelling	It involves presenting behavior for students to imitate, often through demonstrating specific skills for them to observe and replicate.	*"I will show you the steps for adding 2/3 and 1/4. First, I will demonstrate how to find a common denominator."*
R-RR	Response: No Response	It refers to situations where a student refuses to answer questions or remains silent without providing any response.	*"I have no ideas."*
R-SR	Response: Simple Response	It refers to responses that are straightforward but lack depth or thoroughness.	*"Mm, yes, or okay"*
R-FR	Response: Factual Response	It refers to responses that are characterized by their accuracy, reliance on	*"I used the Least Common Multiple (LCM) of the denominators to find a*

		memory, and explanatory nature.	*common denominator when adding fractions”*
R-IO	Response: Interpretive and Open-ended Response	It refers to responses that are detailed and comprehensive, often providing an interpretation or explanation of the information.	*“I think 1/2 and 2/4 are equivalent because they represent the same part of a whole. We can multiply both the numerator and the denominator of 1/2 by 2, then we get 2/4.”*
F-PE	Feedback: Performance Evaluation	It involves providing information about the student’s performance directly to the student.	*“Your calculation is correct. You have done a great job.”*
F-I	Feedback: Instruction	It involves directing students on what actions to take and briefly explaining the reasons behind them.	*“When we add fractions with different denominators, the first step is always to find a common denominator. This helps us make sure the fractions are equal parts, so we can add them accurately.”*
F-E	Feedback: Explanation	It involves providing more detailed information or clarification to enhance students’ understanding of concepts.	*“When the denominators are the same, the fraction with the larger numerator is greater because you have more pieces of the same size. But when the denominators are different, we need to make them the same before we can compare. This is why we find a common denominator, which helps us see the size of each piece more clearly.”*

3.5 Data Analysis

The coded data were further categorized into two groups: the more effective tutoring group and the less effective tutoring group. This classification was based on the presence of two specific indicators. As previously discussed, one key behavior of effective tutoring is constructive engagement, such as students’ self-explanation (Zhang et al., 2021). This type of engagement is often initiated by questions posed by the teacher (Cukurova et al., 2022). In our coding scheme, this behavioral pattern is represented by a transition from the teacher’s initiation of questions (I-Q) to the student’s interpretative and open-ended response (R-IO).

Another important behavioral pattern is the scaffolding sequence, where a focused question, an incorrect answer, a scaffold by giving hints can be observed in order (Molinari et al., 2013). This sequence is captured by the following codes: the teacher’s initiation of questions (I-Q), the student’s factual response (R-FR), the teacher’s feedback on student performance (F-PE), and the teacher’s provision of hints (I-H) to help students actively progress through their problems.

In this study, two distinct groups were formed based on the two behavioral patterns of effective tutoring. The first group, comprising 8 tutoring videos, demonstrated the occurrence of both behavioral patterns and was thus categorized as the more effective tutoring group. The second group, consisting of 12 tutoring videos, did not show these patterns and was categorized as the less effective tutoring group. A total of 2,373 behavioral codes were collected from the more effective tutoring group, while 893 codes were collected from the less effective tutoring group. LSA was subsequently applied to the dialogue data from each group. The analysis aimed to uncover and compare differences in dialogue patterns between the two groups. The results of this analysis are presented and discussed in the following section.

4. Results and Discussion

LSA was conducted on both the more and less effective tutoring groups to examine and compare their behavioral patterns. Using GSEQ 5.1 software, we generated behavioral transition diagrams by analyzing the frequency transitions and adjusted residuals (z-scores) for each group. Sequential behaviors with z-scores exceeding the significance threshold of 1.96 were included in the transition diagrams, as illustrated in Figure 1 and Figure 2. These diagrams visually represent the significant behavioral sequences, with arrows indicating the direction of each transition.

While the general behavioral patterns of both groups were comparable, significant differences emerged in specific areas of interaction. In particular, the strategies for initiating dialogues and managing unresponsive student scenarios differed significantly between the groups. For instance, the more effective tutors typically employed modeling techniques (I-M) to initiate dialogues, a practice not observed in the less effective group. An excerpt from a more effective tutoring session illustrates the use of modeling techniques: "*We now know we need to subtract five-eighths from one. How do we do that? Like we mentioned earlier, one can be written as a fraction with same numerator and denominator. So, we can rewrite one as eight-eighths. Then, subtract five-eighths from eight-eighths. Since the denominators are the same, we subtract the numerators: eight minus five equals three, giving us three-eighths. Does that make sense?*"

Moreover, when faced with students who did not respond to questions, the more effective tutors employed a variety of scaffolding techniques, including posing more targeted questions (R-RR → I-Q), providing direct instruction (R-RR → F-I) or hints (R-RR → I-H). In contrast, the less effective tutors primarily relied on providing hints alone (R-RR → I-H) in similar situations. For instance, in a more effective tutoring session, the tutor used direct instruction when the tutee could not provide an answer to the subtraction of two fractions: "*When subtracting two fractions, we need to convert them to have the same denominator. So here, we need to make the denominators the same before performing the subtraction. Are you familiar with the concept of the least common multiple?*". The tutor then followed up with a target question: "*What is the least common multiple of 8 and 6? Is it 8?*" to prompt the tutee to think about the calculation process.

Furthermore, differences were also pronounced in the follow-up actions after providing feedback on student performance. More effective tutors employed diverse scaffolding methods, such as posing additional questions (F-PE → I-Q), providing explanations (F-PE → F-E), or giving further hints (F-PE → I-H). Conversely, less effective tutors mainly continued with further questions (F-PE → I-Q) after initial feedback. For instance, in a more effective tutoring session, the tutor further explained an alternative method to determine $\frac{1}{4}$ and $\frac{7}{28}$ are equivalent after the tutee multiplied $\frac{1}{4}$ by 7 to get $\frac{7}{28}$: "*When we look at the fraction $\frac{7}{28}$, we can make it simpler by dividing both the numerator and the denominator by the same number. In this case, we divide both by 7. So $\frac{7}{28}$ becomes $\frac{1}{4}$, which is the same as the first fraction. We'll apply this same simplification process to compare the next set of fractions.*".

These findings underscore the critical role of employing varied and adaptive tutoring strategies to effectively engage and support students. The more effective tutoring sessions demonstrated the ability to dynamically adjust instructional approaches in response to the real-time needs of students. By actively recognizing when a tutee was struggling or succeeding, these tutors were able to provide appropriate interventions, such as demonstrating skills, offering hints, or asking targeted questions to encourage deeper thinking and understanding.

For chatbot design, these findings suggest focusing on adaptive strategies that mimic a human tutor's flexibility. The chatbot should identify key behaviors, such as confusion or the need for support, and adjust its responses accordingly. This may include asking follow-up questions, offering step-by-step guidance, or giving hints to help students overcome challenges and progress in their learning.

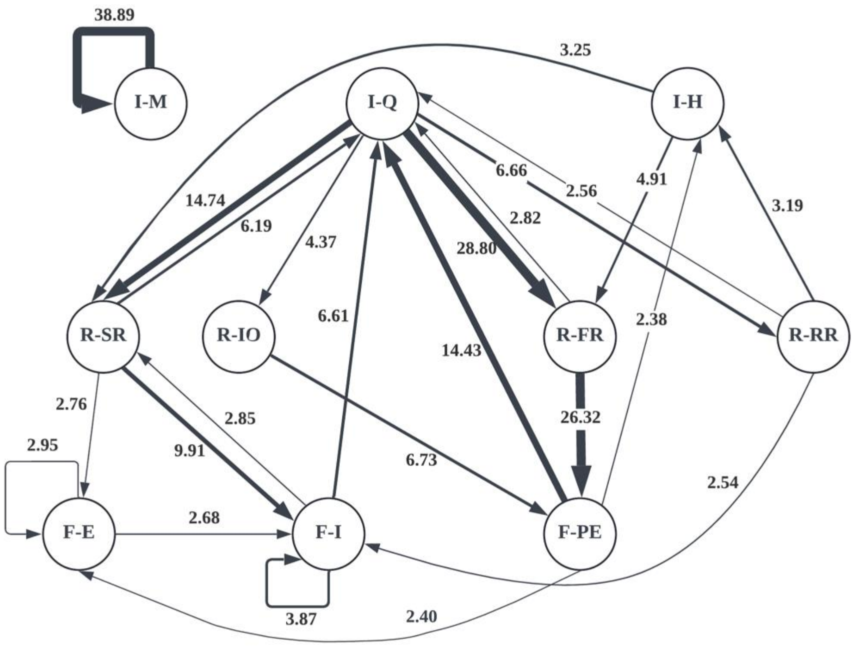

Figure 1. Behavioral Patterns of the More Effective Tutoring Group.

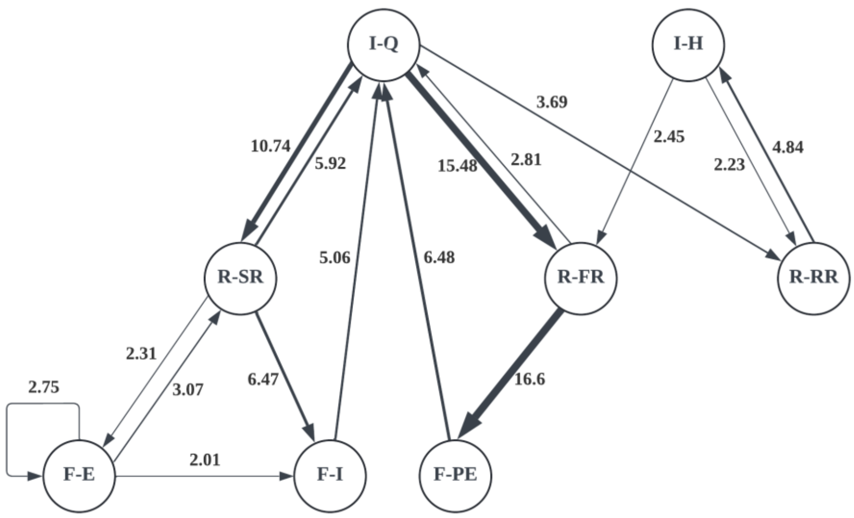

Figure 2. Behavioral Patterns of the Less Effective Tutoring Group.

5. Conclusion and Future Work

The present study aimed to investigate the differences in teacher-student dialogue patterns between more and less effective tutoring groups using lag sequential analysis (LSA).

Specifically, the study focused on one-on-one, tutee-centered online tutoring centered on the topic of fractions in primary mathematics. Two distinct groups were formed based on two behavioral patterns of effective tutoring: self-explanation and teacher scaffolding. The more effective tutoring group demonstrated the occurrence of both behavioral patterns, while the less effective tutoring group did not show these patterns.The results showed that tutors from the more effective tutoring group employed varied strategies for initiating dialogues and managing unresponsive students, including targeted questions, direct instruction, and hints. Additionally, these tutors used a wider range of scaffolding techniques following feedback, such as posing additional questions, providing explanations, and offering further hints. These findings highlight the importance of adaptive and varied instructional strategies in effective tutoring, particularly in the context of online primary mathematics education.

While these findings are promising, they also point to several important directions for future research. First, expanding the dataset by including a larger and more diverse sample of tutoring sessions could yield more robust and generalizable insights into effective tutoring strategies. A broader dataset would allow researchers to capture a wider variety of learning contexts, improving the applicability of the results across different student populations and subject areas.

Second, incorporating human expert evaluations to assess the quality of online tutoring sessions—rather than relying solely on pre-defined indicators—could offer a more nuanced understanding of what constitutes effective tutoring. Expert evaluations could complement the existing metrics, capturing more qualitative aspects of interaction. Furthermore, this approach could aid in collecting high-quality dialogue data from exemplary tutoring sessions, which would be invaluable for fine-tuning the performance of an AI-powered chatbot.

Moreover, future research could focus on the development of an AI-powered chatbot designed to provide adaptive scaffolding, grounded in a strong pedagogical framework. This chatbot could integrate effective tutoring strategies, enabling it to offer personalized support to students at any time, in any location. Such a tool would be particularly valuable in addressing gaps in access to quality tutoring, making learning more inclusive and flexible.

Lastly, conducting a comparative study between AI-driven tutoring and human-led tutoring, evaluated by human experts, could provide critical insights into the strengths and limitations of AI in education. This comparison could highlight areas where AI excels, such as scalability and real-time adaptation, and where a human tutor remains essential (e.g. in addressing the affective domain). These findings would inform the future integration of AI technologies in educational settings.

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