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Preservice Teachers' Dialogue with AI-Powered Virtual Student Agents: Patterns and Perceptions

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This case study reports on the perceptions and dialogic behaviors of 15 preservice K-12 teachers engaging in simulation-based teaching practice with AI-powered student agents. Data included transcripts of text-based classroom dialogue, interviews, observations, and conversation logs. Using mixed-methods analyses and a framework of ambitious science teaching, we identified two key findings that are important to human-AI interaction between researchers and teacher trainers. First, AI-powered student agents exhibit naturalistic discourse behavior, with ambitious talk moves leading to more rigorous student contributions and conservative talk moves leading to low rigor contributions. And second, preservice teachers' dialogue was responsive to the AI-powered students' contributions.

Simulation-based learning is supported by the idea that knowledge development and skills acquisition arise from practice-oriented, experiential learning. Kolb's (1984) experiential learning cycle posits that knowledge is both formed and continuously modified through experience in a cyclical process. A key aspect of teacher education, then, is to facilitate the generation and modification of knowledge and skills in situated contexts until learners have the self-efficacy to apply that knowledge in novel contexts. Successful learning transfer occurs from thorough and diverse practice in contexts that approximate real-life applications (Perkins & Salomon, 1992). Simulation-based learning for teacher training provides a safe, contextualized opportunity for preservice teachers to practice and reflect on knowledge and skills applications so that they can enter real-world classrooms with confidence.

Simulations are models of natural or artificial systems that can be used in education and training for the approximation of real-life practices and exploring the relationships of variables within systems (Heitzmann et al., 2019). Simulating the experience of teaching has become a common practice in preservice teacher training that circumvents the cumbersome nature of in-situ experiences. Simulations in teacher training can range from role playing among peers (Clapper, 2010) to high-immersion virtual reality (VR) environments (Huang et al., 2023). Simulating various scenarios that preservice teachers may encounter in their professional practice has been shown to promote reflectivity (Hixon & So, 2009), teaching self-efficacy (Theelen et al., 2019), and pedagogical knowledge (Mikeska et al., 2023).

Simulation training for preservice teachers has been administered using a variety of technologies. Some of these technologies allow preservice teachers to interact with virtual students that are preprogrammed with automated responses or puppeteered by a human actor (e.g., Mikeska et al., 2023). Recently, simulation technologies have been designed to include students that are integrated with generative AI to produce more context-aware, individualized dialogue than can be had from preprogramming or puppeteering (Dai et al., 2024). These technologies have paved the way for extensive dialogic teaching practice.

AI-integrated teacher training simulations can be used to strategically enhance the educational impact of teacher preparation programs by affording much-needed teaching practice (Loewenberg Ball & Forzani, 2009; Pitura et al., 2024; Zhang et al., 2024a) where preservice teachers can exercise the theory they have learned in a risk-free environment (Dai et al., 2023). AI-powered student agents can be leveraged in these environments to provide authentic interactions where preservice teachers' talk move choices are a key factor for generating academically productive discourse. Language use in classroom interactions plays an important role in student learning as it is the primary medium through which knowledge and ideas are transmitted and negotiated (Mercer & Littleton, 2007). The heuristic nature of dialogic teaching means that the perceived authenticity of simulated interaction with AI-powered student agents is particularly important. Despite this promise, the novelty of AI-powered agents in teacher training simulations has created a need for purposeful explorations to foster better understanding.

AI-powered agents in simulation-based training have also opened a novel and important pathway for furthering the understanding of phenomenologically situated human-AI interaction (Harrison et al., 2007), which drives at individuals' subjective and idiosyncratic experiences. Therefore, the purpose of the current case study is to explore the dialogic behaviors of preservice teachers in interaction with AI-powered student agents during simulation-based teacher training.

Specifically, our study addresses the following research questions:

1. What are the talk move patterns between preservice teachers and AI-powered student agents?
2. What are the perceptions of preservice teachers regarding interacting with AI-powered student agents?

Related Work

Ambitious Science Teaching as a Framework for STEM-based Classroom Dialogue

Science teaching requires the flexible use of teaching strategies to support learning through intentional, dialogic communication. The conversations between teachers and students in the science classroom should cultivate understanding of knowledge, support evidence-based argumentation, and foster a deeper grasp of science concepts (Reznitskaya & Gregory, 2013). Ambitious Science Teaching (AST) is a K–12 STEM teaching initiative that aims to support these goals (Windschitl et al., 2018). According to Windschitl et al. (2018), AST practices focus on drawing out students' explanations of the everyday world as a foundation for instruction. These explanations are then challenged and refined through interaction-rich discussions, with an emphasis on rigorous explanatory dialogue as a key driver of science learning. This can be contrasted with anachronistic science teaching practices that tend to be monologic, with the teacher seen as the sole source of knowledge and students as receptacles for this knowledge (Freire, 1970).

Concerning classroom discourse, AST has been decomposed into individual talk moves that can be used by teachers to engage students with science concepts and support their ongoing thinking as they work toward theorized explanations of those concepts (Windschitl et al., 2018). For instance, ambitious talk moves include "probing questions" that seek to elicit student ideas, and "pressing students for explanations" of scientific phenomena. Ambitious talk moves can also include discussion facilitation by, for example, "distributing participation" to other students as a strategy to garner different perspectives, or "revoicing" student contributions to emphasize key words or anchor students on certain ideas. On the other hand, there are conservative talk moves that tend to hinder rigorous science talk. "Mini-lectures" are one such conservative talk move, which occur when a teacher simply provides information to students, situating the teacher as the authoritative source of knowledge. Asking "display questions" is also an example of a conservative talk move, as these only require short, factual responses that are unlikely to lead to rigorous science talk. The use of the AST dialogic talk moves by preservice teachers has been shown to positively influence the explanatory rigor of young science students (Barnes et al., 2022; Grinath & Southerland, 2018). From this framework, we can operationalize AST classroom dialogue in terms of talk move patterns, involving the sequences of teacher and student talk moves.

The concept of AST is contingent on the understanding that students are sources of rich understanding and are capable of explicating this understanding through scientific inquiry (Metz, 2011). Whether preservice teachers maintain this understanding in interaction with AI-powered student agents is unclear, but critical to the success of AI-integrated teacher training simulations.

Simulation for Teacher Training

Simulated teaching training is a powerful tool for preservice teachers that allows theory application practice or practice managing difficult situations in environments similar to reality but without the need to involve human students. Furthermore, teacher training simulations have been shown to have a large positive effect on the acquisition of complex skills (Chernikova et al., 2020). Teaching simulations vary in composition and complexity, but a key aspect is the simulation of a student (VanLehn et al., 1993). Computer-based simulations of students typically involve student modeling with artificial intelligence (Käser & Alexandron, 2024).

Researchers have explored the use of various AI-powered agents in education. A meta-analysis by Dai et al. (2024) examined the impact of AI-powered virtual agents on learning outcomes in 22 studies and reported a medium positive effect. They noted higher explanatory power for AI technologies like module-based AI, including student modeling, and for studies that used natural language processing.

Multiple teaching simulation tools have arisen over the past few years, such as simSchool (Christensen et al., 2011) and SimStudent (Matsuda et al, 2015). SimSchool is a commercially available tool that employs student modeling through an algorithm of cognitive and affective variables such as openness to learning, extroversion, and persistence (Christensen et al., 2011). Studies of simSchool reported mixed results, with some preservice teachers split on its perceived usefulness (Rayner & Fluck, 2014), and others reporting satisfaction from the increased opportunities for experimentation (Lee & Ahn, 2021). SimStudent used machine learning to create a teachable agent that inductively applied learned rules to solve problems and then adaptively responded to preservice teachers' feedback (Matsuda et al., 2010).

Exploring other tools, a study by Lee and Yeo (2024) used an in-house developed AI chatbot for teachers to practice responsive teaching in mathematics. They used IBM Watson Assistant, a supervised machine learning model, to train their chatbot to recognize question types and numerical entities. Their chatbot was capable of emulating student discourse through text and performed well helping teachers practice responsive teaching.

Researchers have begun to explore the use of generative AI for teacher training simulations. For example, Zhang et al. (2024b) conducted a mixed-methods study exploring the impact of generative AI-powered student agents on preservice teachers' responsive teaching practices in a 3D virtual simulation. They found that preservice teachers leveraged the design features of the AI-powered student agents to coordinate discussions and iteratively practice natural interactions. They also found that preservice teachers considered the AI-powered student agents to be authentic, and the teaching practice to be similar to their experiences practice-teaching in real-world classrooms. Another study by Dai et al. (2024) used a case study method to investigate generative AI-powered student agents in VR-based teacher training simulations. Their conclusions were that student teachers valued the AI-integrated simulation training opportunity and that they found AI-powered student agents' use of humor helped facilitate situational teaching practice. Last, Markel et al. (2023) used GPT-3 to create unique student personas for teacher training in a text-based simulator. They found that the text-based interface helped lower participant stress as it gave them time to think before responding, allowing them to use approaches that were appropriate to the learning goals. However, they noted that it was difficult to emulate a student using a GPT, with students straying from their persona and using language uncharacteristic of a student.

According to Chernikova et al. (2024), a key aspect of simulation-based training is the authenticity of the simulation, where it was found that higher authenticity was associated with higher learning gains. Valid student modeling is one part of authentic teaching simulations (Käser & Alexandron, 2024), but situating the simulation experience in a realistic and immersive environment is also important. This concept is grounded in the theory of experiential learning, where initial concrete experiences in simulated environments can lead to active experimentation and meaningful learning (Kolb, 1984). The use of virtual reality technology in teaching simulation is becoming more common as the technology has become more sophisticated and prevalent (Huang et al., 2023; Wang & Li, 2024). 3D virtual environments for teacher training simulation can evoke a sense of presence in users, allowing them to experience the performative nature of teaching while also impacting their behavior similarly to how being in a real teaching environment might (Huang et al., 2023). These affordances have been associated with improved classroom management, teaching self-efficacy, and reflective skills (Wang & Li, 2024). Building on the reviewed literature, AI-integrated simulations appear to offer authentic, low-risk spaces for preservice teachers to rehearse complex classroom skills. Recent studies suggest that AI-powered student agents can sustain plausible, responsive participation in instructional exchanges. Yet, across this work, not much is known of the fine-grained dialogic mechanics of those exchanges, such as the patterns of academic talk moves that surface when preservice teachers interact with AI-powered student agents, and how they experience those interactions. Prior findings on authenticity and the mixed perceptions of teacher trainees motivate a closer look at the discourse itself (RQ1) and preservice teacher perceptions (RQ2). By addressing these questions, we can move beyond global outcomes of simulation-based teacher training and toward evidence that links spoken classroom interactions with user experience.

The authentic and immersive nature of AI-integrated teacher training simulations creates opportunities for naturalistic dialogue to emerge between teacher trainees and AI-powered student agents, impelling a close examination of those interactions. To illustrate how talk moves unfold in these circumstances, and to document whether preservice teachers perceive those exchanges as useful, credible, and transferable, the present study analyzes the frequent patterns of talk moves in teacher-agent discourse and investigates teachers' perceptions of those interactions.

Method

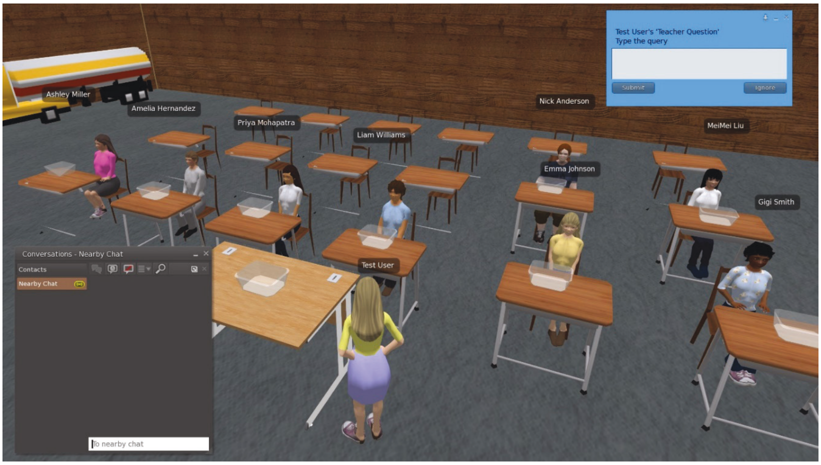
We adopted a mixed-methods case study design (Yin, 2018) to address the two research questions in a context-rich, in-depth, and in-situ manner. We utilized both qualitative and quantitative methods to analyze the interactions between preservice teachers and AI-powered student agents during simulation-based teacher training.

Design of the Teacher Training Simulation and AI-powered Student Agents

This study used The Enactive Virtual Environment for Teaching practice (*EVEteach*), a classroom teaching simulator with AI-powered student agents (Ke et al., 2021). *EVEteach* utilizes *OpenSimulator*, an open-source virtual world platform, to render a 3D virtual classroom environment (Figure 1). The environment supports omnidirectional movement of a user's avatar, artifact interaction, and text-based communication (Fishwick, 2009).

Figure 1

SIM Environment with AI-Powered Students and Teacher Avatar



Note. Dialogue history box is shown at the bottom-left, and the text input box is shown at the top-right.

The *EVEteach* environment is populated with intelligent virtual agents modeled to look and talk like middle school students. The student agents were integrated with a customized version of generative pretrained transformer-2 (GPT-2), a model chosen for its susceptibility to training data and low hallucination rate compared to more recent LLMs (Luo et al., 2024; Xie et al., 2022). To approximate the discourse of middle school science students, the GPT was pretrained using authentic classroom discourse from transcriptions of over 30 science and math classroom recordings involving in-service teachers and human students (Bhowmik et al., 2022). These recordings are publicly available from various online sources such as Ambitious Science Teaching (www.ambitiousscienceteaching.org) and Trends in International Mathematics and Science Study (TIMSS; nces.ed.gov/timss). This pretraining established a baseline for knowledge and linguistic expressions typical for middle school science students. The agent architecture was further bolstered with a characterizing prompt that fine-tuned the output by limiting the GPT's tendency towards volubility and formality. Last, a short-term memory was included so that context-aware discussions with the agents could progress. A visualization of the agents' architecture can be found in Figure 2, and Figure 3 depicts the program-level architecture.

Figure 2

Architecture of the AI-powered Student Agent

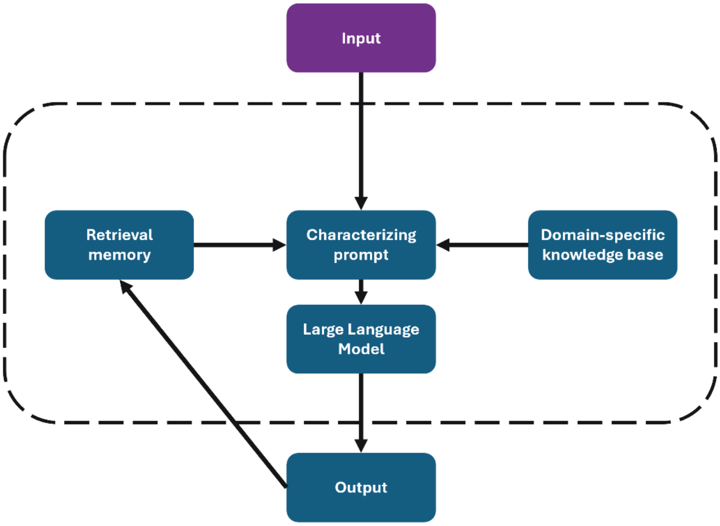
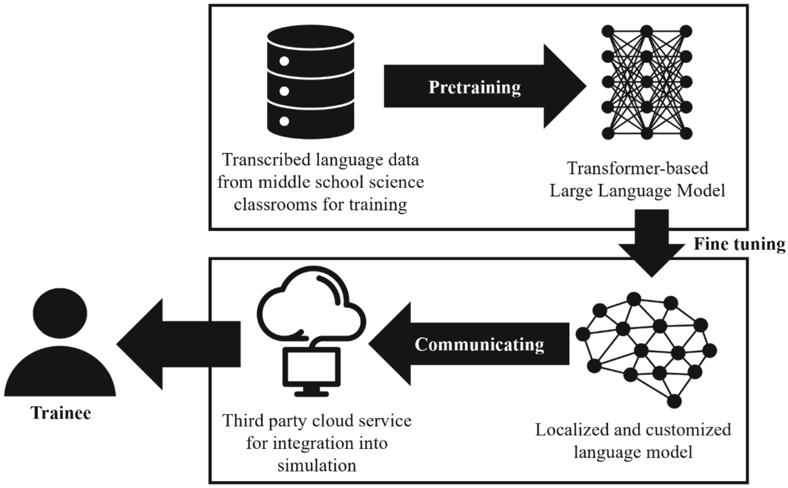


Figure 3

Architecture of the SIM System



Extensive alpha and beta testing was conducted on SIM to investigate its validity as a teacher training tool. Bhowmik et al. (2024) conducted alpha testing on the agent's adaptability to evolving classroom discussions by measuring recall rate and accuracy after several rounds of dialogue. They found the agent capable of accurately recalling previous dialogic contingencies after multiple turns at talk. A study by Barrett et al. (2024) compared the AI-student agents' discourse to the human students in the pretraining corpus and found that agent discourse within the simulator closely approximated the discourse of the human students along specific talk moves. Another study by Barrett et al. (2025) examined the probability of talk move transitions and found that AI students were more likely to provide rigorous science explanations when stimulated with ambitious science talk moves, a dynamic that was also observed in real classrooms with human students. Ultimately, SIM has shown promise as a teacher training tool that simulates middle school science student discourse behaviors with reasonable accuracy.

Participants

Fifteen preservice teachers (all female) were recruited through voluntary self-selection to participate in this study. These participants were enrolled in a science teacher preparation program at a college of education at a public university in the southern United States. All participants provided written consent to partake in the study and to have their data anonymously recorded in accordance with the ethics requirements of the university.

Procedure and Data

Participants were scheduled for a two-hour session with a facilitator. Sessions were held over Zoom, and participants interacted with the simulator through remote control of the facilitator's computer. Each session began with an orientation to the simulation environment and AI-powered student agents. Participants were allowed to choose a science or math topic to teach (e.g., fungi, gas laws, line graphing), which they were asked to introduce to the AI-powered students and worked to build a consensus around. During the session, participants were encouraged to think out loud by the facilitator to capture their teaching decisions and their impressions of the AI-powered students' responses (Van Someren et al., 1994). This involved the facilitator using prompts such as "Why do you think the student said that?", "What do you think that means?", and "What do you think is the best way to respond to that?" At the end of each session, the facilitator conducted a short unstructured reflective interview focusing on the participants' experience with questions about their perceived fidelity of the AI students and their perceived usefulness of the simulator.

During the simulation, participants interacted with the AI-powered student agents by typing queries into a dialogue box. Queries could be directed at individual students or to the whole class. AI student responses to each query were printed in an on-screen dialogue box; student silences were printed as such. A typical dialogue is illustrated by the example below from participant 4.

P4:	Does anybody knwo [*sic*] anything about fungi?
AI student:	Um, they can change.
P4:	Thats [*sic*] good. Does anyone else have any thing to add?
AI student:	Kevin?
P4:	Has anyone ever had a mushroom before?
AI student:	Yeah, so they just like... break stuff down and make you sick.
P4:	Why do you say they make you sick?
AI student:	Because they make me sick.
P4:	So Linda had a good point by saying they break stuff down. Does anyone else have anything to add to this?
AI student:	Uh, I think that was more for, um, uh, protection than anything.
P4:	What do you mean by that?
AI student:	Like, like, when it's rotting it starts to get really old and then like, it starts rotting again.

Data for this study included video and audio recordings of the Zoom sessions, which captured the participants' qualitative impressions, and transcripts of the text-based interactions between the participants and the AI-powered student agents. These transcripts totaled 23,734 words across 2,431 turns of talk.

Discourse Coding and Reliability

Discourse interactions between the preservice teachers and AI-powered student agents were coded by two researchers using an ambitious science talk move framework adapted from Barnes et al. (2022) and Teo (2016), which can be found in Table 1. This framework categorizes teacher discourse moves as ambitious or conservative, and ranks student moves as being more or less rigorous. Following AST theory, we consider academically productive discourse to consist of ambitious talk moves which lead to high-rigor student contributions (Windschitl et al., 2018).

Using a systematic process to establish coding reliability, two researchers conferred on the meaning of each talk move extensively before individually coding the same 10% of the data. They then discussed any discrepancies in their coding until they reached complete agreement and felt comfortable coding the remaining data. Regular meetings were held to discuss uncertainties that arose during independent coding until all data were coded. This process resulted in 2,638 coded talk moves between preservice teachers and AI-powered student agents.

Table 1

Teacher and Student Talk Moves

Role	Category	Talk move	Code	Explanation
Teacher	Ambitious	Acknowledge contribution	Tac	Recognizing a student talk move without indicating correctness, demonstrating active listening.
		Counterclaim	Tcc	Presenting students with an alternative perspective.
		Distribute participation	Tdp	Encouraging contributions to the classroom discussion from other students.
		Press for explanation	Tpe	Pursue more rigorous thinking by eliciting additional meaning.
		Probing question	Tpq	Broadly questioning students to elicit ideas or thoughts.
		Revoice	Trv	Echoing or paraphrasing a student contribution in part or in whole. Used to summarize, connect, clarify or emphasize what students said.
	Conservative	Display question	Tdq	Requesting a single, obvious, or expected answer.
		Evaluate correctness	Tec	Assessing a student contribution as correct or incorrect.
		Minilecture	Tml	A provision of information that explains lesson content.

Role	Category	Talk move	Code	Explanation
Student	Less rigor	Silent (no student talk)	Sst	No student talk.
		Definition/ Fact	Sdf	Short, factual answers.
		Description/ Observation	Sdo	Relaying an observation or description of a phenomenon or personal experience without providing an explanation.
		Question	Sqn	An interrogative, seeking information from the teacher.
	More rigor	Under theorized science explanation	Sue	Describing a phenomenon or experience as part of a simple process or system and inferring what is happening at an unobservable level.
		Fully theorized science explanation	Sfe	Connecting a phenomenon or experience to a scientific theory, model, or law beyond simple processes or systems.

Data Analysis

To address research question 1, we examined the talk move frequency of individual participants in addition to an apriori association rule mining algorithm (Raschka, 2018) to identify patterns of talk moves. Apriori association rule mining is a data mining technique that identifies frequent patterns of items in large datasets. Patterns are organized into antecedents and consequents, where given the presence of an initial item or group of items (antecedent), a likelihood of a consequent item or group of items can be calculated with an "if X then Y" metric. Using this analysis, we can, for example, identify if teacher probing questions are followed by student theorized explanations, along with the probability of such an occurrence.

For the pattern analysis, we filtered results by lift, a metric that indicates the likelihood of a consequent occurring given the antecedent compared to its overall likelihood of occurring. Our analysis set a lift threshold of 1. Lift values greater than 1 mean the antecedent increases the likelihood of the consequent occurring. We then conducted two searches to find semantically appropriate and meaningful interactions between preservice teachers and the AI-powered student agents. One search looked specifically for productive academic discourse, which we defined as patterns with an ambitious or high-rigor consequent. The second search looked specifically for academically unproductive discourse patterns, defined as those with conservative or low-rigor consequents. We also include confidence values for identified patterns, which indicate their reliability. Confidence is calculated as the proportion of patterns containing the antecedent that also contain the consequent. In other words, it indicates the likelihood that talk move(s) Y occurs given the occurrence of talk move(s) X. To illustrate, if an X→Y pattern has a confidence score of 0.6, it means that 60% of the time that X occurs, Y also occurs. The formulas for lift and confidence are given below in relation to "support," the total number of interactions containing X divided by the total number of interactions:

$$Lift(X \rightarrow Y) = \frac{Support(X \cap Y)}{Support(X) \times Support(Y)}$$

$$Confidence(X \rightarrow Y) = \frac{Support(X \cap Y)}{Support(X)}$$

To answer the second research question, the qualitative data were analyzed for references to interactions with the AI-powered agents. Specifically, we looked for possible explanations or insight for the occurrence of academically productive or unproductive patterns in discourse between preservice teachers and AI-powered student agents. We compared information across participants using iterative immersion in the data (Patton, 1999), selectively identifying data points that addressed our research purpose. This process produced nascent findings that informed the nature of the interactions between the preservice teachers and AI-powered student agents.

Results

Data Descriptives

A descriptive appraisal of talk move frequencies for each participant is available in Figure 4. Preservice teachers frequently utilized ambitious science talk moves during simulation-based training with AI-powered student agents. Probing questions were the most used ambitious talk move, followed by acknowledging contributions and then pressing for explanations. Counterclaims were the least utilized ambitious talk move.

Conservative talk moves were also used by preservice teachers, with minilectures being the most common. Display questions and evaluating correctness were rarely used by preservice teachers.

Looking at individual participants, a high variation in talk move usage is evident. For instance, participants 5 and 11 demonstrated heavy reliance on minilectures, using that talk move for 69% and 75% of their total talk, respectively. This is in stark contrast to participants 7, 8, 10, and 12 who never used minilectures. Participant 11 had marginal use of ambitious science talk moves, accounting for only 17% of their total talk, whereas participant 1 used conservative talk moves only 11.8% of the time.

Figure 4

Heat Map of Talk Move Frequency and Percent (Rounded) for Each Preservice Teacher, with Means and Standard Deviations

	Ambitious talk moves						Conservative talk moves			
Participant	Acknowledge contributions	Counterclaim	Distribute Participation	Press for explanation	Probing Question	Revoice	Display Question	Evaluating Correctness	Minilecture	**Total**
P1	6 (9%)	1 (2%)	5 (7%)	4 (6%)	32 (46%)	12 (18%)	2 (3%)	1 (2%)	5 (7%)	68
P2	22 (18%)	1 (1%)	10 (8%)	4 (3%)	20 (16%)	6 (5%)	3 (2%)	5 (4%)	55 (43%)	126
P3	12 (14%)	1 (1%)	7 (8%)	7 (8%)	42 (47%)	5 (6%)	5 (6%)	4 (4%)	5 (6%)	88
P4	16 (25%)	1 (2%)	15 (23%)	3 (5%)	20 (31%)	4 (6%)	0 (0%)	2 (3%)	3 (5%)	64
P5	2 (2%)	1 (1%)	0 (0%)	1 (1%)	18 (22%)	2 (2%)	1 (1%)	1 (1%)	59 (70%)	85
P6	5 (3%)	2 (1%)	5 (3%)	20 (11%)	143 (76%)	7 (4%)	2 (1%)	0 (0%)	1 (1%)	185

	Ambitious talk moves						Conservative talk moves			
Participant	Acknowledge contributions	Counterclaim	Distribute Participation	Press for explanation	Probing Question	Revoice	Display Question	Evaluating Correctness	Minilecture	**Total**
P7	17 (19%)	2 (2%)	7 (8%)	11 (12%)	43 (48%)	9 (10%)	1 (1%)	0 (0%)	0 (0%)	90
P8	21 (19%)	1 (1%)	9 (8%)	13 (12%)	54 (47%)	13 (12%)	0 (0%)	1 (1%)	0 (0%)	112
P9	17 (17%)	0 (0%)	7 (7%)	8 (8%)	42 (42%)	1 (1%)	4 (4%)	3 (3%)	18 (18%)	100
P10	2 (7%)	0 (0%)	1 (3%)	2 (7%)	24 (77%)	1 (3%)	1 (3%)	0 (0%)	0 (0%)	31
P11	0 (0%)	0 (0%)	0 (0%)	4 (7%)	5 (9%)	0 (0%)	0 (0%)	5 (9%)	42 (75%)	56
P12	6 (22%)	0 (0%)	2 (7%)	5 (19%)	13 (48%)	1 (4%)	0 (0%)	0 (0%)	0 (0%)	27
P13	6 (9%)	1 (2%)	2 (3%)	1 (2%)	22 (31%)	0 (0%)	0 (0%)	10 (15%)	26 (38%)	68
P14	10 (9%)	0 (0%)	11 (10%)	13 (12%)	26 (23%)	3 (3%)	2 (2%)	7 (6%)	39 (35%)	111
P15	4 (3%)	0 (0%)	4 (3%)	14 (12%)	33 (27%)	10 (8%)	4 (3%)	14 (12%)	38 (32%)	121
Total	146 (11%)	11 (1%)	85 (7%)	110 (8%)	537 (40%)	74 (6%)	25 (2%)	53 (3%)	291 (22%)	1332
M (SD)	9.73 (7.3)	0.73 (0.7)	5.67 (4.4)	7.33 (5.7)	35.8 (32.4)	4.93 (4.4)	1.67 (1.7)	3.53 (4.1)	19.4 (21.8)	88.8 (40.2)

Talk Move Patterns

The association rule mining analysis identified over 350 unique talk moves patterns that resulted in both academically productive and unproductive discourse between the preservice teachers and AI-powered student agents. Table 2 shows patterns of productive academic discourse. Preservice teachers who utilized ambitious talk moves often received high-rigor student contributions. Teacher probing questions (Tpq) and pressing for explanation (Tpe) appear the most in the antecedents of the identified academically productive talk patterns. Lift values for identified patterns were between 1.86 and 2.84 (from a curated range of 1.2 to 3.4), showing that utilizing these antecedents made it likely for the consequents to occur. It is also evident that high-rigor student talk moves were followed by ambitious teacher talk moves, suggesting mutual reinforcement. Two identified patterns which resulted in student under-theorized science explanations (Sue) had confidence levels at or above 75%, meaning that those antecedents were particularly useful in drawing out high-rigor contributions.

Table 2

Talk Move Patterns between Preservice Teachers and AI-Powered Student Agents with Ambitious or High-Rigor Consequents

Antecedent	→	Consequent	Confidence	Lift
Tac + Tpe	→	Sue + Tdp	0.2	2.839
Tpe + Tdp	→	Sue + Tac	0.294	2.193
Tpq + Sdo + Tac + Tpe	→	Sue	0.818	2.034
Tdp + Sue	→	Tpe	0.419	1.942
Tdp + Sdo + Tpe	→	Sue	0.75	1.864

Table 3 shows the unproductive talk move patterns identified in the data. Antecedents in these identified patterns tended to contain conservative talk moves, such as teacher minilectures (Tml) and teacher display questions (Tdq). These antecedents had a high likelihood to result in student silences (Sst), students providing definitions or facts (Sdf), or teacher minilectures (Tml). The talk move pattern Sdo + Tec + Sqn → Tml had a confidence of 89% and a lift of 2.3, indicating that teachers evaluating correctness (Tec) in conjunction with low-rigor student contributions such as observations (Sdo) are highly likely to result in teacher minilectures (Tml). Teacher minilecture (Tml) plus a display question (Tdq) resulted in student silence (Sst), a pattern that had a lift value of 3.2, demonstrating that this teacher talk combo was not engaging for the AI-powered students.

Table 3

Talk Move Patterns between Preservice Teachers and AI-Powered Student Agents with Conservative or Low-rigor Consequents

Antecedent	→	Consequent	Confidence	Lift
Tml + Tdq	→	Sst	0.5	3.235
Sqn + Tdp	→	Sdf	0.238	2.619
Sdo + Tec + Sqn	→	Tml	0.889	2.314
Tpq + Sdo + Tml	→	Sst	0.278	1.797
Tdq + Sst	→	Tml	0.625	1.627

Preservice Teacher Perceptions of Interacting with AI-Powered Student Agents

To better understand the dialogic interactions between preservice teachers and AI-powered student agents we analyzed the session and interview transcripts for instances where participants provided insight into their experiences with the AI students and simulation. Two salient ideas were identified through qualitative analysis: perceived authenticity of interactions with the AI-powered student agents, and the influence the AI-powered student agents had on preservice teachers' decision making.

Perceived Authenticity of AI-Powered Student Agents. Preservice teachers seemed split on the authenticity of the AI-student agents' responses. Several preservice teachers commented that the AI-student agents were similar to human students. For example, participant 2 said "the virtual students are very similar to actual students in the ways they interacted with the teacher and how they ask questions of clarification." This sentiment was echoed by participant 5, who stated "some of the responses were very on par with what I was teaching, and they helped me extend my lesson because I had something to build off of."

Several other preservice teachers commented that the AI-powered student agents' responses seemed inauthentic. For instance, participant 4 felt "like the students don't know what they're responding to." Likewise, participant 13 said "it was hard to know if the responses from the students were an artifact of the VR simulation or deliberately included as a disruption to the flow of conversation," suggesting that she was second-guessing the AI-powered student agents. However, participant 4 also stated that the seeming randomness of the AI-powered student agents' responses helped her practice extemporaneous teaching, stating that "the simulation can help teachers think of what to do when students don't respond how they were expecting."

Multiple preservice teachers noted that the AI-powered student agents were unable to converse with each other. An illustrative comment was made by participant 15 who stated, "they are able to facilitate a conversation with me, but they didn't facilitate a conversation with each other, which is kind of unrealistic." This signifies a design issue of the simulation program where the AI-powered student agents could only receive input from the preservice teacher and were not programmed to respond to each other as human students would when the teacher is facilitating a class discussion.

The Influence of AI-Powered Student Agents on Preservice Teacher Talk Moves. What was evident from the descriptive analysis of preservice teachers' talk move frequencies (Table 2) was the disparity between those who chose to use ambitious talk moves and those who chose to use conservative talk moves. In examining the qualitative data, it was evident that preservice teachers were, in part, making discourse decisions in response to the AI-powered student agents' contributions. How they decided to respond influenced whether the discussions were academically productive or not.

Looking for responsive teaching that led to academically productive discourse, several preservice teachers provide illustrative examples. Participant 4 (who primarily utilized ambitious talk moves) explained how she decided to distribute participation to other students when she felt like one student was struggling to understand: "if she didn't understand it, there was no point in me just hassling her over it and, like, just keep asking the same question if she didn't understand it. So I made the decision, I guess, to open that question up to the whole class. And then when someone responded to that question, I started talking to them more to try to continue the discussion." Another participant (P7, who also used more ambitious talk moves) described how she tested a variety of strategies when she perceived the discussion going off track: "I definitely learned that, like, spontaneous thoughts will just come out of the class basically, and you have to try different tactics in order to get the class back on track… I tried asking them to stop or appeasing them and going along with their train of thought, and then also ignoring it altogether… I tried to see what topics they introduce and kind of go with them. Like go along with it. I got some good responses that made me feel like they understood.” To illustrate how participant 7’s discourse decisions steered the discussion toward more academically productive talk an excerpt from the student-teacher transcript is shown in Table 4. For each turn at talk, participant 7 used probing questions to mine for student resources that could be expanded on to build consensus on the topic. Even when the AI-powered student agents started asking questions, participant 7 responded with questions of her own or revoiced the student questions to see how the class might answer them. This strategy ultimately paid off in line number 14 where the student provides an extended contribution that gives the teacher insight into their understanding and provides resources that the teacher could use to better shape the discussion (e.g., “growing on things” and “rot”).

Table 4

Excerpt from Transcript Between Participant 7 and AI-Powered Student Agents

#	Speaker	Turn at talk
1	P7	Does the size of the fungi matter?
2	AI student	No.
3	P7	What does the size of the chain mean then in terms of fungi size?
4	AI student	Um, because there’s different numbers.
5	P7	What are different numbers Michael?
6	AI student	What’s different?
7	P7	How do mushrooms make simple sugars?
8	AI student	How do fungi make sugar?
9	P7	Why do fungi make sugar?
10	AI student	Why do they make that terrible smell?
11	P7	Why do they make that terrible smell?
12	AI student	Because it’s like ... it’s gross.
13	P7	Sometimes fungi can be gross I agree, but I wonder why we think it smells?
14	AI student	Because we’ve only got like two-thirds of the year so we’ve got to see if it rots or if it grows on things. Because fungi are gross, so if it’s growing on things it must be growing on them.

Not every preservice teacher opted to use ambitious talk moves in response to student contributions. One example of how this occurred was illustrated by participant 11, who said "I keep rephrasing what they're saying, to try to get them there, but sometimes, like, I had to just tell them, like, certain facts that they didn't know. Because they just— they weren't gonna get there on their own, they needed to, like, know the facts." Here, participant 10 indicated that they would use minilectures to provide information when they felt that the students were not understanding something. Responding to students' perceived confusion by using minilectures was also a strategy used by participant 14, who stated "the questions would initiate more responses, but that doesn't necessarily mean that the responses will be accurate. So I think the way that they learned best was explaining it to them very thoroughly." An excerpt from participant 5's session (Table 5) provides insight into how minilecturing can perpetuate. The expert begins with the participant minilecturing, but in line number 5, she attempts to move away from minilecturing by asking a probing question; however the student responds to the question with a question of its own. The participant then resorts to more minilecturing to answer the students' questions.

Table 5

Excerpt from Transcript Between Participant 5 and AI-Powered Student Agents

#	Speaker	Turn at talk
1	P5	Some mushrooms and truffles can be eaten.
2	AI student	Any other ways fungi affect you?
3	P5	Some fungi can negatively affect you.
4	AI student	Okay, good.
5	P5	In what ways do you think fungi can harm you?
6	AI student	How do they impact you when you first acquire it?
7	P5	One way fungi can negatively affect you is in the form of mold. If someone is around too many mold spores, it can adversely affect their breathing.
8	AI student	Mhmm.
9	P5	Some fungi are poisonous and cannot be ingested.

Discussion

This case study closely examined the dialogic behaviors of 15 preservice teachers in interaction with AI-powered student agents during simulation-based teacher training. The study's purpose was to better understand how AI-powered student agents were perceived by preservice teachers and how those perceptions might have influenced AST practice.

In attendance to our first research question, the dialogue between the preservice teachers and the AI-powered student agents adhered to expected patterns of AST discourse. Specifically, when preservice teachers utilized ambitious talk moves such as probing questions or pressing for explanation, it was likely to generate more academically productive discourse from the student agents. Additionally, conservative talk moves such as minilectures had the opposite effect, stymieing academically productive discourse. These findings exhibited the authenticity of the dialogic interactions during simulation-based training and the utility of generative AI-powered student agents. The stochastic nature of generative AI is reflected as adaptivity in the student agents who are capable of generating different answers to preservice teacher input depending on how that input is framed. A minilecture is designed to relay information and facts and in using that talk move a preservice teacher does not expect the student to reason but to absorb the facts. Conversely, pressing students for explanations is a talk move designed to elicit evidence of student reasoning. When confronted with these talk moves, the student agents in this study tended to respond accordingly. Previous studies that involve simulation-based teacher training in mixed-reality environments often reported a lack of student authenticity due to preprogramed or scripted student responses (Ade-Ojo et al., 2022). This study contributes to the literature by demonstrating how AI can be integrated into student agents for more authentic interactions.

Regarding our second research question, the preservice teachers had mixed impressions of the AI students. Discourse choices made by the preservice teachers appeared to be influenced by the perceptions of AI-powered student agent discourse. This indicates the utility of AI-powered simulation for responsive teaching practice and supports the findings of Zhang et al. (2024b) and Zhang et al. (2025) who found that preservice teacher behavior was influenced by whether the simulated students' discourse was aligned with the lesson target outcome or whether they were silent or off topic. This also suggests the possibility of design-based solutions that can support preservice teachers during the simulation. Instead of relying on reflective practice to identify areas for improvement, such as, for example, where minilecturing was being perpetuated, in-virtuo cues or supports can be included such as those suggested by Alkan et al. (2024) and Huang et al. (2024). For instance, a pop-up can occur when too many declarative statements are made, and this scaffold can be gradually reduced as teachers progress in their training; or less conspicuously, communicated through agent behavior, where AI students visibly lose interest in the lesson as more minilecturing occurs.

In general, this study showed that preservice teachers had mixed perceptions of the AI-powered student agents, with some focusing on the simulation limitations and others viewing the students as authentic and interacting with them contextually. Illustrative of the latter is participant 4's comment that she didn't want to "hassle" the AI-powered student agents over their lack of understanding, demonstrating a propensity to interact with the agent empathetically, supporting more responsive discourse (Jaber et al., 2023). Likewise, participant 14's comment about "the way that they learned best" showed how she was evaluating the perceived learning style of the agent and how that appraisal influenced her dialogue. These interactions demonstrated how the AI-powered student agents supported the kind of agile pedagogical reasoning and decision-making that occurs in real classrooms (Thompson et al., 2016).

Conclusion, Limitations, and Future Research

This study offers important insight in human-AI interaction. First, the AI-powered student agents in our study afforded natural and authentic dialogic interactions that supported ambitious science teaching practice. Preservice teachers were able to use ambitious talk moves and experience how that dialogue generated academically productive discourse. Second, our findings showed that the contributions of the AI-powered student agent influenced preservice teachers' pedagogical decision-making, but these decisions seemed contingent on the preservice teachers' awareness and empathy. When confronted with student questions, some teachers succumbed to minilectures whereas others continued to probe for ideas. Last, and related to the previous takeaway, high authenticity may only be beneficial in simulations that utilize closely monitored reflective practice. A more academically beneficial teacher training simulation should have dynamic learning supports designed into it.

The contributions this study made to the literature on AI-powered agents should be considered alongside some key limitations. Primarily, the

AI technology used in this study is not as powerful as more recent models. Although this also affords a design advantage that allows the student agent to exhibit realistic deficits in science knowledge, future research should explore whether this can be achieved with the latest models. Additionally, we ensured transferability by using researcher reflexivity and attention to context, however, some aspects of our data analysis were unavoidably subjective. The methodology used in this study allowed for an in-depth analysis of preservice teacher discourse behavior and perceptions. However, it does not afford the generalizability or insight that a controlled experiment might; this is further confounded by our self-selection sampling technique and all female participants. Last, limitations of the simulation program can impact its authenticity. For instance, the program does not allow for student-to-student interaction and is limited to text-based interactions. Despite these limitations the findings of this case study provide important insights into preservice teacher interactions with AI-powered student agents.

Future research endeavors in AI-integrated teacher training simulations could extend the findings from this study by examining how agent non-linguistic behaviors, such as body language or facial expression, might provide preservice teachers with insight into learner affective states, and how that insight might influence discourse behaviors. Furthermore, although the text-based communication system allows for preservice teacher processing time, having vocal interactions with the agents could provide insight into heuristics while also more accurately reflecting real classrooms.

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