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Exploring the Design of Pedagogical Agent Roles in Collaborative STEM+C Learning

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Abstract: This paper explores the design of two types of pedagogical agents—*teaching* and *peer*—in a collaborative STEM+C learning environment, C2STEM, where high school students learn physics (kinematics) and computing by building computational models that simulate the motion of objects. Through in-depth case study interviews with teachers and students, we identify role-based features for these agents to support collaborative learning in open-ended STEM+C learning environments. We propose twelve design principles—four for teaching agents, four for peer agents, and four shared by both—contributing to foundational guidelines for developing agents that enhance collaborative learning through computational modeling.

Introduction and Background

During collaborative problem-solving (CPS), students use dialogue to externalize and pool knowledge, justify their choices, and construct a shared understanding (Roschelle & Teasley, 1995). Extensive research highlights the advantages of collaborative learning in STEM+C (Science, Technology, Engineering, Mathematics, and Computing) environments (Snyder et al., 2019; Hutchins et al., 2020), which foster learning, problem-solving, and critical thinking (Grover & Pea, 2013). While these benefits are significant for complex tasks like computational model building, they introduce greater cognitive demands (Hutchins et al., 2020), underscoring the need to identify student difficulties and provide adaptive support in collaborative settings (Andrini, 2023).

Vygotsky's (1978) *zone of proximal development* emphasizes the importance of guided support in helping learners accomplish tasks they cannot yet complete independently. However, designing effective pedagogical support is complex, requiring consideration of students' prior knowledge, progress in their problem-solving tasks, conversations, affective states, and body language (Cohn, Snyder, et al., 2024). In classrooms, teachers lack the bandwidth to monitor the cognitive, metacognitive, and social dimensions of students' group conversations and problem-solving progress in computer environments (Wambsganss et al., 2021).

Pedagogical agents can bridge this gap by managing interactions with multiple student groups simultaneously. *Teaching agents* "play the role of human teachers" (Kuhail et al., 2023), delivering explanations, examples, and immediate feedback; while *peer agents* serve as learning companions, fostering peer-to-peer interactions and guiding students along learning paths (Kuhail et al., 2023).

Elshan & Ebel (2020) identified design principles for their collaborative peer agent, Timmy, suggesting agents in collaborative settings should enhance perceptions of "humanness and social presence." Nguyen (2023) focused on design considerations for teaching and peer agents while students worked in groups to build a conceptual map of a marine ecosystem. While both agents improved student learning, Nguyen (2023) found that the peer agent facilitated more transactive exchanges and was rated as more sociable compared to the teaching agent.

Recent research has similarly focused on enhancing teaching agents with human-like qualities to improve their sociability, such as offering encouragement and celebrating learners' progress (Jurenka et al., 2024). Google's LearnLM-Tutor, a teaching agent spanning several domains (e.g., biology, math, history, computer science), incorporates insights from participatory and co-design activities with teachers and students (Jurenka et al., 2024). Their design principles suggest that teaching agents should "see what the student sees."

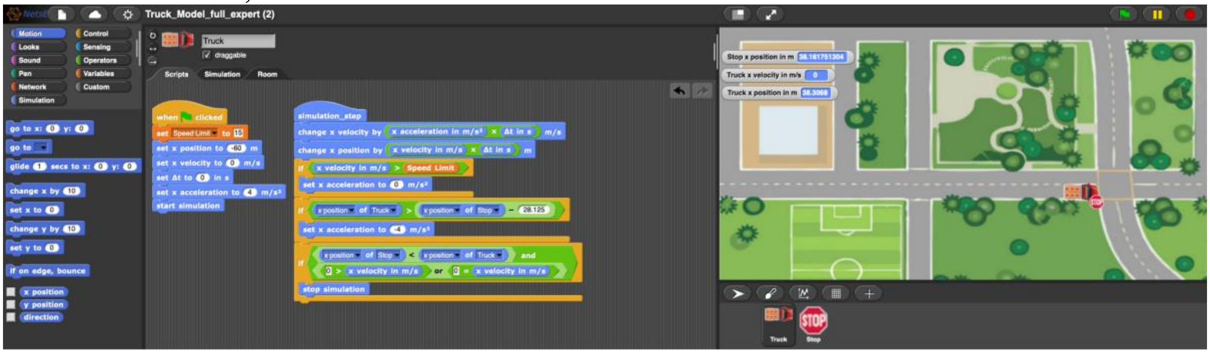
Despite extensive research investigating the roles of agents as both teachers and peers (Kuhail et al., 2023; Zhang et al., 2024; Sikström, 2024; Dai et al., 2022), previous studies have not established feature sets for agents in collaborative settings (Nguyen, 2023). This study addresses this gap by conducting *semi-structured interviews* with teachers and students to identify role-based features for teaching and peer agents in open-ended, collaborative STEM+C environments for high school students. Using these features, we derive 12 design principles for these two types of agents: four for teaching agents, four for peer agents, and four shared by both.

Methods

C2STEM Learning Environment and Truck Task

C2STEM is a collaborative, block-based coding environment that teaches high school students to integrate physics and computing knowledge through problem-solving (Hutchins et al., 2020). In the *Truck Task*, students model a truck starting from rest, speeding up to the speed limit, cruising at the speed limit, and decelerating to stop at a stop sign. Figure 1 presents a snapshot of C2STEM and an "expert" Truck Task model.

Figure 1
C2STEM Environment, Truck Task



Experimental Design

We conducted semi-structured case study interviews with three students and two teachers in Nashville, TN, USA to identify agent features and design principles, audio-recording all conversations. The five participants varied in race and gender (Black, White, Hispanic; male, female), spoke fluent English, and had prior experience with C2STEM. Students were aged 16-17, and teachers had 15-20 years of teaching experience. Each 45-minute session followed a consistent protocol, presenting participants with two video scenarios (2-4 minutes each) showing different student dyads encountering difficulties with the Truck Task. The videos combined student webcam (audio and video) footage and screen recordings of their actions within the environment. To inform the design of the teaching agent, we asked teachers to describe how they identified student difficulties and would implement appropriate interventions to help the students. For the peer agent, we asked students to specify their preferences for how a peer agent should detect challenges and intervene effectively. This study was approved by Vanderbilt University's Institutional Review Board, with all participants (teachers, students, and their legal guardians) providing consent and assent. We describe our interview protocol in the Supplementary Materials.

Raw audio from each session was transcribed using Otter.ai, with researchers manually correcting errors. Teacher and student utterances containing key insights were memoed (Hatch, 2002) and coded by discussion topic by two researchers with extensive knowledge of the C2STEM curriculum and environment. Coding was *inductive*, using *multi-label consensus coding* (i.e., assigning multiple codes to a single utterance with agreement from both researchers), grounded in prior CSCL research (Chen et al., 2019). The same coding scheme was applied to teacher and student conversations to ensure a consistent basis for comparing agent features. Both researchers discussed, refined, and reached a consensus on each utterance's codes through multiple iterations. In total, 88 (43 teacher and 45 student) utterances were extracted. To identify the design features for each agent, the two researchers analyzed the frequency and content of the coded utterances.

Results

Codes

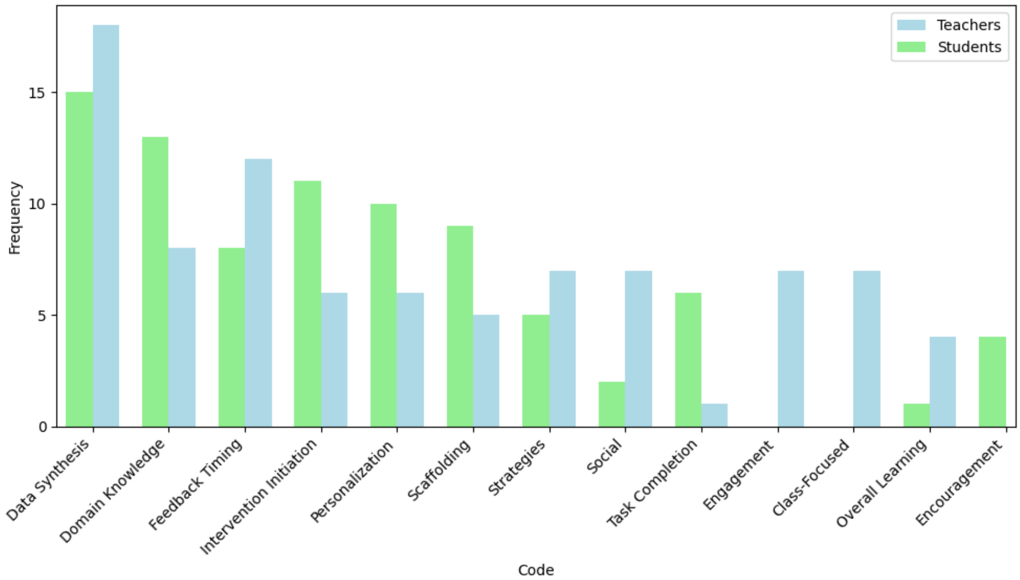
Our analysis resulted in thirteen codes, presented with definitions, frequencies, and utterance examples in our Supplementary Materials. Each utterance received an average of two codes, resulting in 176 total codes across all 88 utterances. Figure 2 presents the codes and their frequencies for teachers and students.

Features and Design Principles

Teachers and students exhibited substantial overlap in their discussions about how their respective agents should interact with students, highlighting several shared features between the two types of agents. *Data Synthesis* was the most prevalent code (see Figure 2) for both teachers and students, with each discussing how the data could be analyzed to detect student difficulties and inform agent intervention decisions. Both groups referenced a range of data modalities, including affect ("...he's frustrated…"), environment actions ("...they decide to open up the graph…"), and discourse ("...in their dialogue, 'oh' is, like, a very common word…").

Figure 2

Teacher and Student Code Distributions (sorted by total code occurrence)



Both groups also identified *Domain Knowledge* ("What physics needs to take place…") and *Feedback Timing* ("...give them time to figure it out…") as important factors guiding agent interventions, agreeing that 1) students' understanding of physics and computing should be factored into agent interventions, and 2) students be allowed the opportunity to overcome difficulties on their own before an agent intervenes. Although less frequent, teachers and students also viewed problem-solving *Strategies* as valuable for informing interventions from both agents, particularly noting "trial-and-error" as a poor strategy indicative of students being lost ("…they're just clicking random stuff…"). These findings underscore four key design principles essential for both teaching and peer agents: 1) integrate ***diverse data inputs*** to capture multiple aspects of students' states (e.g., domain knowledge, cognitive/metacognitive processes, affect); 2) account for students' current ***domain knowledge*** when designing interventions; 3) ***delay feedback*** after detecting difficulties, allowing students to first address challenges independently; and 4) be attentive to students' ***problem-solving strategies***, addressing ineffective approaches.

Despite these similarities, notable differences emerged in the design preferences for the two types of agents. *Teachers took a more holistic approach* to intervention administration, thinking beyond the specific domain- and task-related knowledge required by individual students. Teachers emphasized the *Social* dimension of collaborative problem-solving three times as often as students, viewing collaboration quality as essential for effective interventions ("...we really want to get peers communicating with each other to solve these problems…science is done collaboratively…"). They also expressed a desire to support student learning more broadly (*Overall Learning*) rather than simply helping students accomplish the Truck Task ("I want that to also be a practice that they would engage in. I think that would be valuable…"; "…I believe in a lot of, sort of, active learning…").

A similar trend emerged regarding the intended recipients of interventions. Teachers preferred *Class-Focused* strategies to benefit students as a whole ("I think I would want to do that with everyone…"). Teachers also saw student *Engagement* as a critical indicator for guiding interventions ("...somebody, like, disengaging from the computer…")—a factor students did not consider. These findings highlight four design principles specific to teaching agents: 1) incorporate ***social awareness*** by considering students' interactions and promoting collaboration; 2) support the development of generalizable problem-solving skills and ***broader learning*** goals beyond the immediate task; 3) analyze aggregated learning metrics to inform teachers of ***classroom trends***; and 4) design interventions that consider and address student ***engagement***.

Unlike teachers, students adopted a narrower focus, concentrating on peer agent interactions tailored for individual students or dyads (*Personalization*; "...give suggestions based on…like, what [students] say…"). They focused on the Truck Task (*Task Completion*; "...more specific to this task…"), rather than on broader learning goals. They frequently referenced *Scaffolding*, emphasizing their preference to avoid receiving direct answers from an agent ("...again, not giving them like a direct answer, but trying to keep them on the right path…"). Students did not emphasize *Social* interactions as something the peer agent should consider when identifying student difficulties or formulating intervention decisions, nor did they wish for the agent to encourage more effective collaboration; in fact, one student explicitly stated that it would be "embarrassing to get called out" if a peer agent were to imply that the students were not collaborating well.

Students highlighted the importance of having agency in deciding when the peer agent would intervene ("…bring it out as, like, the user pleases…"), placing considerable emphasis on who (agent or student) initiated the intervention (*Intervention Initiation*)—a priority mentioned more than twice as often by students than by teachers. Although students generally preferred agent-initiated interventions ("...the agent should almost be able to kind of intervene once they see, like, repetitive actions being made…"), they also valued the option for student-initiated interventions to verify code and confirm that they are on the right track ("...an option for…when they feel confident that [the code] is right, be able to…say, like, is this correct?"). Reassurance and *Encouragement* were also discussed several times by students ("...reassuring them that they're on the right track…"), as they felt peer agents should encourage students even when not encountering difficulty. Based on these insights, the design principles specific to peer agents are as follows: 1) tailor interactions to individual students and dyads, ensuring interventions remain ***focused on completing the task at hand***; 2) ***scaffold interventions*** by providing guidance without revealing answers directly; 3) grant students ***agency over the timing and initiation*** of agent feedback; and 4) offer ***emotional support*** to reassure and encourage students**.** In our Supplementary Materials, we use a Venn diagram to present each agent's design principles visually.

Discussion and Conclusions

Our findings underscore the distinct roles of teaching and peer agents in collaborative STEM+C settings. Teachers' focusing on the social dimension of CPS highlights the critical role of student interactions in shaping effective agent interventions, aligning with *social constructivist* principles that underscore interaction, dialogue, and shared experiences in constructing knowledge (Vygotsky, 1978). Assessing collaboration quality using social metrics such as *equity* and *turn-taking* scores (Cohn, Snyder, et al., 2024) could enhance an agent's ability to effectively intervene. Teachers' emphasis on engagement highlights the importance of teaching agents that target curricular and collaborative goals and sustain student motivation, aligning with Dai et al.'s (2022) concept of a *mentor agent*.

Peer agents should prioritize a task-oriented focus while delivering personalized feedback that addresses students' academic and emotional needs. Elshan and Ebel (2020) stress the importance of agent "humanness and social presence," which our peer agent findings reflect. Student emphasis on reassurance also aligns with Jurenka et al. (2024), reinforcing the need for instructional supports that act as social agents rather than mere conveyors of domain knowledge. The value students place on agency in peer agent interactions highlights the importance of tailoring these agents to meet individual learners' and groups' specific needs and preferences. However, as Cohn, Snyder, et al. (2024) highlight, the *specificity–scalability* trade-off in human-centered design poses challenges, requiring a balance between catering to individual preferences and developing scalable solutions.

Despite their distinct roles, several design features were shared by both agents. Students and teachers stressed the importance of using multiple modalities when detecting difficulties and designing interventions, echoing Jurenka et al.'s (2024) "see what the student sees" principle. Recent research on multimodal learning analytics (MMLA) emphasizes the value of integrating modalities such as speech, logs, text, and affect, which provide deeper insights into student behaviors and outcomes than unimodal approaches (Cohn, Davalos, et al., 2024). The desire for delayed feedback was similarly expressed for both agents, aligning with previous work that characterizes this "delay" as the *feedback latency interval* separating two inflection points—a *difficulty threshold* when students encounter a challenge and an *intervention point* when a teacher intervenes (Cohn, Snyder, et al., 2024).

These findings have broader implications for students' interactions with intelligent systems in collaborative settings. There is a need to adapt intervention timing and triggers to develop more dynamic and personalized support for students—an area where MMLA is particularly well-suited. Collaboration should be positioned as a transferable skill, akin to problem-solving, which traditional intelligent tutoring systems often overlook (Elshan & Ebel, 2020; Nguyen, 2023). Cohn, Snyder, et al. (2024) characterize the relationship between humans and technology as a "co-regulation" where both parties adapt and change based on the other's needs. As we continue exploring various ways to enhance computer-supported collaborative learning, we will better understand the interplay of teaching, learning, and social factors in technology-enhanced environments.

Finally, this work is not without limitations. Our study sample included five participants (three students and two teachers) whose data was self-reported, limiting our findings' generalizability. In the future, we will conduct classroom studies to explore how agents designed using these principles influence student collaboration, learning outcomes, and emotional responses to feedback, as well as identify which agent features support students in CSCL environments optimally.

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