A GenAI Programming Tutor with a Social Robot Interface: A Mixed-Methods Pilot on Theory of Mind Attributions and Technology Acceptance*

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Abstract

Recent advances in Generative AI (GenAI) have enabled new forms of intelligent tutoring systems, yet most AI-based programming tutors remain screen-bound and text-based. Social robots offer a physically embodied presence that can influence learner engagement, motivation, and perceptions of the tutor. To explore the educational potential of combining these two approaches, this study introduces a GenAI-driven tutoring environment, specifically developed for this research. The system integrates a GenAI-based programming tutor with a GenAI-based social robot, embodied in the NAO humanoid robot, to investigate how embodiment shapes students' perceptions of a programming GenAI-based tutor from the lens of Theory of Mind (ToM) and Technology Acceptance Model (TAM). The system provides learners with short programming challenges and adaptive tutor-feedback generated by GenAI. Learners interact with the platform through a structured web interface that supports code writing in a designated IDE. In the embodied social robot condition, the same tutor responses are delivered by the robot through speech and body gestures. In the chat condition, feedback is presented entirely through text. In this mixed-method pilot study (N=14), the robot version of the GenAI programming tutor received significantly higher ratings on all Theory of Mind factors, especially perceived awareness of the student's cognitive and emotional state. Both modalities scored high on TAM, but the robot was seen as more useful and elicited higher intention to use, with no ease-of-use difference. Qualitative feedback shed light on the reasons for these effects. Although preliminary, the findings indicate that embodiment may add relational value, especially around perceived awareness and emotional support.

Keywords

Social Robot, GenAI, Theory of Mind, Technology Acceptance Model, Computer Science Education, AIED

1. Introduction

Programming demands abstract reasoning, structured problem-solving, and meticulous attention to detail, which often challenge novice learners, increase cognitive load, and induce anxiety [1], [2]. To address these challenges, Generative AI (GenAI)-based tutoring systems have been increasingly utilized [3], [4] to provide personalized guidance, instant feedback, and flexible explanations through conversational interfaces [5], [6], [7]. At the same time, research on social robots in education has demonstrated that physically embodied social robots can boost engagement, motivation, and socio-emotional support during learning [8], [9]. These findings suggest that embodiment may provide additional benefits beyond chat-based AI tutors, particularly when learners encounter demanding tasks such as computer programming.

Building on the theoretical framework of Theory of Mind (ToM) [10] and Technology Acceptance Model (TAM) [11], [12], this study aimed to explore how the tutor modality (chat vs. robot) affects students' perceptions and attitudes toward the tutor. Specifically, this research is guided by the following research questions:

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RQ1. To what extent does the tutor's modality (robot vs. chat) influence students' perceptions of the tutor's ToM, including cognitive understanding and emotional awareness, as well as the perception of the tutor's perception of the student's cognitive and emotional awareness?

RQ2. To what extent does the tutor's modality (robot vs. chat) influence students' perceptions of its perceived usefulness, perceived ease of use, and behavioral intention to use the system, as defined by the Technology Acceptance Model?

2. Theoretical Background

2.1. Social Robots

Social robots are physically embodied agents designed to interact with humans through social behaviors, including speech, gesture, gaze, and emotional expression [13]. They differ from purely functional or industrial robots by their ability to engage in meaningful, human-like communication and to adapt their behavior in response to social cues [13]. In recent years, social robots have been increasingly integrated into educational settings, serving as teaching assistants, peer learners, or motivational companions that support various learning processes [9]. Their embodied nature enables them to convey presence and empathy through multimodal channels, including voice, facial expressions, and body language, thereby creating a sense of co-presence that chat-based interfaces struggle to replicate [14]. These qualities make them particularly relevant for learning situations that require sustained engagement.

Within educational environments, social robots have been shown to improve engagement, motivation, and learning outcomes across various age groups and subjects [9]. By offering real-time feedback, encouragement, and personalized guidance, robots can support both cognitive and socio-emotional aspects of learning [15]. The presence of a robot has also been linked to increased learner attention, positive emotions, and persistence during difficult tasks [16]. These effects are often credited to the robot's physical embodiment, which enables richer interaction and promotes social presence, a factor that influences learning satisfaction and perceived effectiveness [17]. Such effects are particularly relevant for computer programming, where learners frequently experience frustration and require sustained motivation. Understanding how learners perceive and relate to social robots is therefore essential for designing effective robot-mediated learning experiences.

2.2. Technology Acceptance Model (TAM)

TAM suggests that users' intention to adopt a technology is influenced by perceived usefulness (PU), perceived ease of use (PEU), both influencing the behavioral intention to use (BI) [11]. PU indicates how much a user believes the technology will improve performance or aid learning. Conversely, PEU refers to how easy the system is perceived to operate. BI indicates the likelihood that a user will utilize the system in the future. Thus, systems that are helpful, effective, and simple to use tend to be viewed more positively. Another study on telepresence robots in higher education similarly showed that PU was the main direct predictor of students' intention to use these robots, with PEU influencing usefulness and use intention indirectly [18].

Since TAM has been widely used in research on educational and robotic technologies (e.g., [12], [19]), it offers a suitable framework for understanding students' attitudes toward the GenAI-based tutor in both its physical and chat-based versions.

2.3. Theory of Mind (ToM)

Theory of Mind (ToM) is the ability to attribute mental states such as thoughts, intentions, and understanding to others [10], [20]. Originally developed to explain how people predict and interpret human behavior, the concept has since been extended to interactions with artificial agents, including virtual assistants and social robots, where users may similarly infer mental states or understanding based on behavioral cues.

In human–robot interaction, ToM provides a framework for understanding why people may treat robots as intentional or socially aware partners [21]. Behavioral cues such as nodding, pausing, or making eye contact can lead users to infer that the robot understands them, which can increase perceptions of engagement, trust, and social presence [22], [23]. Simulated mental states have been shown to influence human decision-making, collaboration, and willingness to engage with a robot in future interactions [24], [25]. These findings suggest that ToM-related processes play a significant role in shaping learners' experiences with robot-mediated instruction.

At the same time, over-attributing mental states to robots raises ethical concerns. Learners may trust systems that do not truly understand them, potentially blurring the line between tool and companion [26]. In educational settings, this emphasizes the importance of carefully designing social cues and clearly communicating system capabilities. In this study, TAM, which captures users' functional evaluations of usefulness and ease of use, and ToM, which highlights the relational and social dimensions of interaction are used as a theoretical framework to analyze how the tutor's modality, whether delivered through a physically embodied robot or a chat-based interface, shapes learners' experiences in computer science education.

3. Methodology

3.1. Participants

Fourteen participants (5 female, 9 male) from the Faculty of Education in Science and Technology at the Technion – Israel Institute of Technology, took part in an exploratory pilot study. Participants ranged in age from 24 to 58 years ($M = 33.64$, $SD = 12.35$) Self-reported programming experience included beginner ($n=5$), several years ($n=4$), and advanced ($n=5$). Familiarity with AI tools was high (AI use in general: $M = 4.71$, $SD = 0.47$; AI use for programming: $M = 3.86$, $SD = 1.17$). The mean Qualtrics session duration was approximately 30 minutes. Participation was voluntary, no identifying personal information was collected, and the study was approved by the institutional ethics committee. All participants provided informed consent prior to participation.

Sessions were conducted individually in a designated quiet room, where participants interacted with the system alone under controlled conditions. As a token of appreciation, all participants received a small toy robot upon completing the experimental tasks and the accompanying questionnaire and/or interview.

To control for potential order effects, the study used a counterbalanced condition order: seven participants began with the chat condition, while seven participants began with the robot condition.

3.2. Materials

3.2.1. The "May the CODE be with you" Application

The experimental platform is a web-based application designed to give students programming tasks along with automated, GenAI-generated hints and feedback. It can be accessed through any modern web browser and features a structured interface where students select a topic, receive a programming challenge, and interact with the AI tutor throughout the task (see Figure 1).

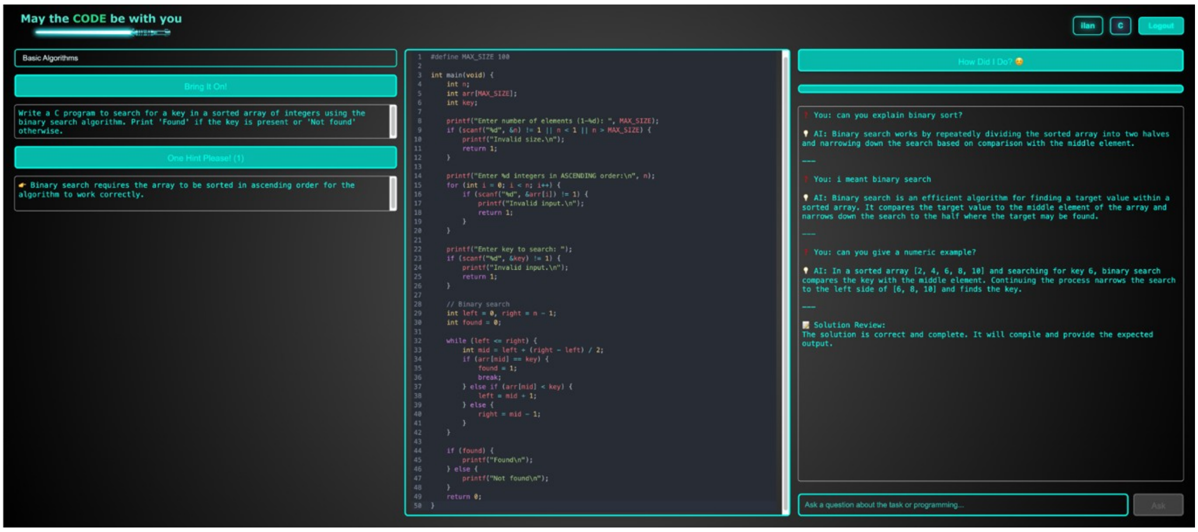

Figure 1. "May the CODE be with you" web application main screen.

Students begin by selecting a programming topic that aligns with the course syllabus. The system then creates a short programming challenge, generated by GenAI, based on the selected topic. Students can ask questions about the task, seek clarifications, or request conceptual explanations through a text input box, and the platform will reply with AI-generated feedback shown in a dedicated feedback panel.

For each challenge, the platform automatically produces a set of GenAI-generated hints tailored to the task. Students may request hints incrementally, and the system provides additional guidance based on their current code and progress. After submitting a partial or complete solution, students receive AI-generated feedback describing errors, misconceptions, or next steps. Importantly, the same challenge content, hints, and feedback are used in both the robot and chat conditions to ensure equivalence across modalities.

The platform features an integrated code editor that provides basic syntax highlighting, allowing students to write their solutions directly within the interface. The editor records students' code submissions and revisions, enabling future analysis of their problem-solving processes.

3.2.2. Nao Robot

The Nao robot is a small humanoid robot developed by Aldebaran Robotics (now SoftBank Robotics). Nao stands about 58 cm tall and weighs around 5.4 kg. Nao is the embodied condition in this study, which is a widely adopted research platform in human–robot interaction and educational robotics [27], [28]. Nao is capable of speaking, gesturing, orienting its head, and displaying expressive body movements. In the present study, the robot vocalizes the GenAI responses produced by the tutoring system and accompanies them with gestures such as nodding, arm movements, and gaze shifts. These behaviors are triggered through a Python-based control interface that relays the system's output to the robot in real time. Importantly, the robot does not interpret student input autonomously; it serves as an embodied delivery mechanism for the same feedback and hints presented in the chat condition, ensuring that instructional content is equivalent across the two modalities.

3.2.3. Software Architecture

Figure 2 illustrates the main components of the system's software architecture. It integrates a social robot through a Python control library wrapped in a local server and exposed via a Flask API. This interface enables remote triggering of the robot's behaviors, including speech and gestures, which deliver the GenAI feedback during the embodied condition. The API supports both low-level motor commands and higher-level behavior scripts, allowing the robot to vocalize responses and use expressive movements. This configuration ensures that the robot reliably reproduces the same instructional content as in the chat condition.

The student-facing interface is a web-based frontend developed in React.js, which displays programming tasks, the code editor, hint requests, and AI-generated feedback. The frontend communicates with the backend to retrieve challenges, submit code attempts, and log user interactions. In the robot condition, it also triggers the delivery of the same generated responses through the robot, ensuring synchronization between visual and embodied feedback.

A central Node.js backend coordinates communication between the web interface, the robot controller, and the learning analytics database. The server generates programming challenges through the OpenAI API, processes students' code submissions, and logs detailed interaction data, including hint requests, solution attempts, timestamps, and navigation events. In the embodied condition, the backend also relays each AI-generated response to the robot controller for vocalization. This centralized orchestration ensures that both conditions receive identical instructional content and enables precise tracking of students' interactions for later analysis.

The system uses the OpenAI API to generate programming challenges, explanations, hints, and contextual feedback in natural language. For each selected topic, the platform generates a standardized challenge and set of initial hints, while additional feedback is dynamically produced in response to students' code and requests.

The platform includes a learning analytics database that records students' interactions with the system, including topic selections, hint requests, code submissions, timestamps, and text queries. These data support internal validation of system behavior and provide contextual information for interpreting questionnaire responses. Although performance outcomes are not the primary focus of the present study, the logged data allow for supplementary analysis of students' interaction patterns.

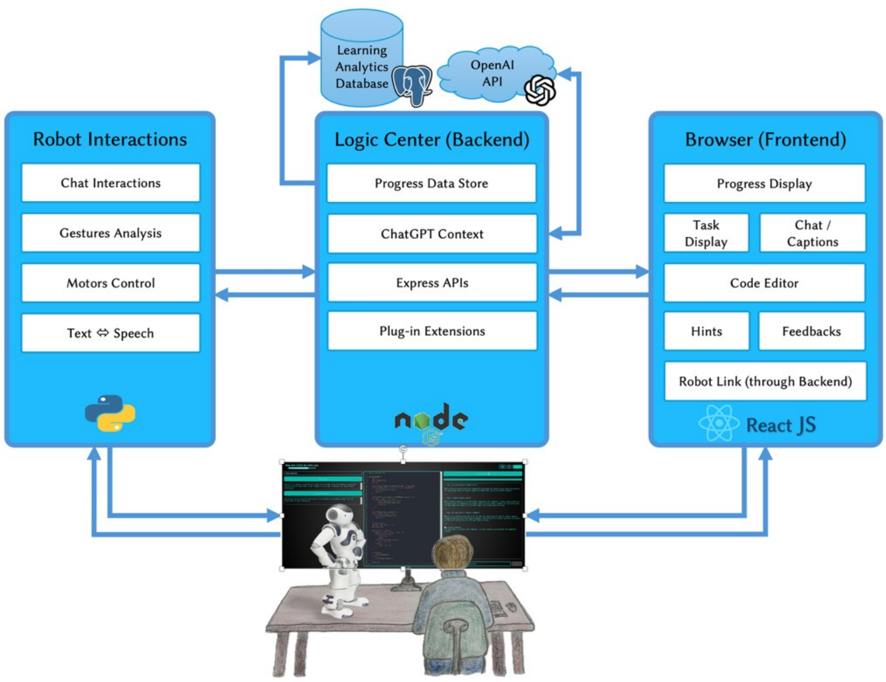

Figure 2. System's software architecture.

3.3. Conditions

The experiment includes two conditions: a Chat condition and a Social Robot condition (see Figure 3). In both conditions, students interact with the "May the CODE be with you" application, receive the same programming challenge, and obtain identical hints and feedback. The only difference between the conditions is the addition of a social robot that can be interacted with verbally in addition to the chat that is displaying the conversation.

In both conditions, all guidance, explanations, and feedback are presented as text within the web interface. In the Robot condition, the same AI-generated responses are simultaneously vocalized by the Nao robot, accompanied by hand gestures, nodding, or orienting its head toward the learner. The robot is positioned on the desk in front of the student, allowing for direct visual and auditory interaction. This setup isolates the effect of physical embodiment while holding instructional content constant across conditions.

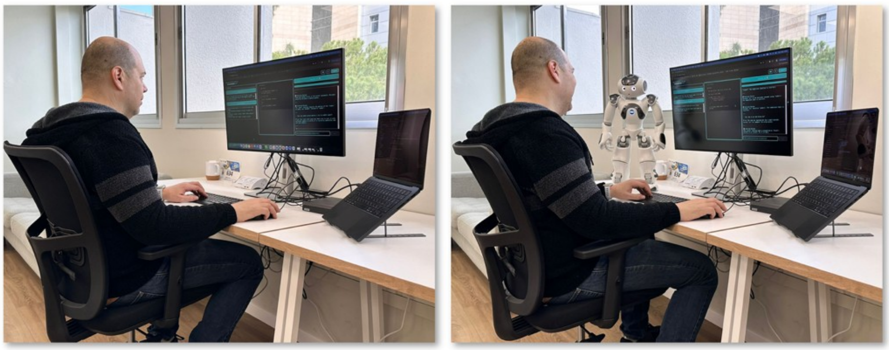

Figure 3. Chat condition (left) and Robot condition (right)

3.4. Measures

3.4.1. Theory of Mind (ToM) Questionnaire

The study employs a 16-item Likert-type questionnaire (1 = strongly disagree, 5 = strongly agree) designed to assess students' attribution of mental states to the AI tutor. The instrument is based conceptually on Theory of Mind research [10] and has been adapted for use with artificial agents in educational and human–robot interaction contexts. The items are organized into four subscales reflecting different dimensions of the student's perceived mental state attribution for: (a) the tutor's cognitive understanding (e.g. "the tutor knows how to solve programming challenges", α=.625), (b) the tutor's perception of the student's cognitive understanding (e.g. "the tutor understands the way I think", α=.713), (c) the tutor's emotional state (e.g. "the tutor is glad when I successfully solve a challenge", α=.566), and (d) the tutor's perception of the student's emotional state (e.g. "the tutor notices my feelings while I am working", α=.757). Each subscale contains multiple items assessing how students interpret the tutor's thoughts, goals, feelings, and awareness (e.g. "The tutor knows how to solve programming tasks").

3.4.2. Technology Acceptance Model (TAM) Questionnaire

A 12-item Likert-type scale (ranging from 1 = strongly disagree to 5 = strongly agree) is used, adjusted from[11], to measure participants' impressions of the system they interacted with. The TAM constructs are (a) Perceived Usefulness (PU) (4 items, e.g., "An AI-based tutor can improve my programming skills", α=.814); (b) Perceived Ease of Use (PEU) (4 items, e.g., "Using an AI-based tutor does not require any special technological skills", α=.682); (c) Behavioral Intention to use the system (BI) (4 items, e.g., "I would use this system in the future if given the opportunity", α=.650).

3.4.3. Demographics Questionnaire

At the end of the session, we asked the users for their age, gender, Academic Degree, Tenure as a Programmer, Level of Hebrew, and Level of English.

3.4.4. Questionnaire - Qualitative Part

To complete our assessment, the participants were asked the following questions:
(a) To learn programming, I would rather study (pick one): (1) alone, (2) with chat, or (3) with robot.
(b) Explain your choice
(c) Which system features assisted learning? Which did less?
(d) If you could change something in the learning manner with such a system, what would it be?

3.5. Procedure

Each participant completed an individual session in a designated quiet room at the Technion. Upon arrival, participants were greeted by the researcher, received a short explanation of the study aims (evaluating two interaction modalities of an AI-based programming tutor), and signed an informed consent form. No identifying personal information was collected. Participants were then introduced to the system interface and were given brief instructions on how to interact with the tutor (e.g., how to submit code, request help, and interpret feedback).

The study employed a within-subjects design in which each participant experienced two tutoring modalities: Chat and Robot. In the Chat modality, participants interacted with the tutor through the on-screen interface without any robot present. In the Robot modality, the same tutoring system was presented with a physically present social robot, which delivered feedback in an embodied manner while the programming activity remained screen-based. To reduce potential order effects, the condition order was counterbalanced: seven participants completed the Chat condition first and seven completed the Robot condition first.

In each condition, participants engaged in a short programming activity aligned with their experience level, during which they attempted to solve the task(s) with support from the AI tutor. The tutor provided guidance such as corrective feedback, hints, and encouragement based on participants' progress. Participants were instructed to work independently and to use the tutor as needed. After completing the activity in each condition, participants completed the corresponding questionnaire measuring their perceptions of the learning experience. When applicable, a brief interview was conducted to gather qualitative impressions and clarify questionnaire responses.

At the end of the session, participants were debriefed and received a small toy robot as a token of appreciation for their time and participation.

4. Preliminary Results

This section reports the early outcomes from the preliminary data collection, combining quantitative questionnaire results with qualitative themes from participants' open-ended feedback. Repeated measures MANOVAs were used to examine the effect of the tutor modality (robot vs. chat) on TAM's and ToM's factors.

ToM showed a significantly stronger robot advantage across all four factors, $F(4,10)=11.612$, $p<.001$, $\eta^2=.823$ (see Table 1, Figure 4). The robot modality was rated significantly higher on both student's perception of tutor's cognitive understanding, $F(1,13)=8.840$, $p=.011$, and the way they perceived the tutor's perception of their cognitive understanding was even more significant with the robot, $F(1,13)=19.925$, $p<.001$. The students also perceived the robot tutor's emotional state to be significantly higher than the chat, $F(1,13)=18.130$, $p<.001$. Likewise, they perceived the robot's ability to understand their own emotional state to be significantly higher, $F(1,13)=13.091$, $p=.003$. Notably, the largest differences emerged in factors that require attributing learner-state sensitivity to the tutor (e.g., "Tutor's Student's Cognitive Understanding" and "Tutor's Student's Emotional Awareness"). Interestingly, although the students were told that they can get hints for the solution by pressing a designated button in the system, they preferred asking the tutor directly, in both modalities.

Table 1. Theory of Mind Means and SD by Robot and Chat (N=14)

	Robot		Chat		
Student perception of:	Mean	SD	Mean	SD	Sig
Tutor's cognitive understanding	4.64	.36	4.34	.50	.011
Tutor's perception of the student's cognitive understanding	3.98	.43	3.07	.85	<.001
Tutor's emotional state	3.5	.54	2.59	.84	<.001
Tutor's perception the student's emotional state	3.25	.55	2.39	.836	.003

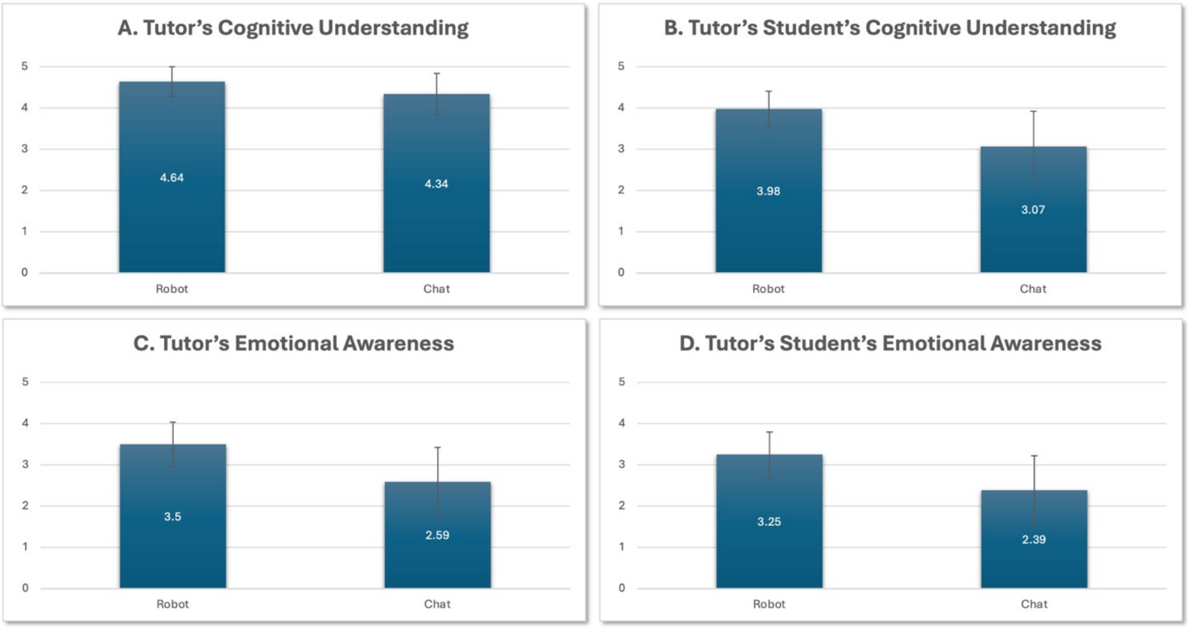

Figure 4. Theory of Mind (ToM) Means and SDs

Regarding TAM, overall the MANOVA results did not yield significant results, $F(3,11)=2.465$, $p=.117$, $\eta^2=.402$. Students reported significantly higher scores of the robot's perceived usefulness compared to the chat, $F(1,13)=8.025$,$p=.014$ (see Table 2, Figure 5). Likewise, students expressed high behavioral intention to use the robot over the chat mode, $F(1,13)=4.987$, $p=.044$. Nevertheless, the students' perception of the robot's ease of use was not significant, $F(1,13)=1.653$, $p=.221$. Across all three measures, the students rated both conditions highly, with scores above 4 out of 5.

Table 2. Technology Acceptance Model Means and SD by Robot and Chat (N=14)

	Robot		Chat		
Technology Acceptance Model (TAM) factors:	Mean	SD	Mean	SD	Sig
Perceived Usefulness	4.51	.47	4.11	.68	.014
Perceived Ease of Use	4.39	.60	4.16	.52	.221
Behavioral Intention to Use	4.57	.49	4.23	.74	.044

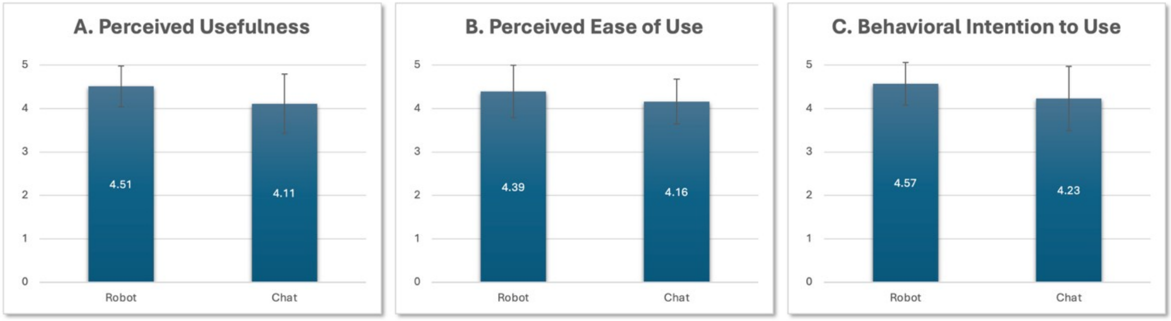

Figure 5. Technology Acceptance Model Means and SDs

Furthermore, we conducted a thematic analysis of the open-ended responses to the question "What is your preferred tutor modality and why?". Interestingly, all 14 participants selected the robot as their preferred modality. We identified three recurring themes with respect to their explanation of their choice: (1) Easier to communicate verbally than textually, (2) A robot feels like someone is with you, and (3) A robot can make you feel better.

(1) *Easier to communicate verbally than textually* – participants repeatedly described the benefit of speaking naturally while coding and receiving immediate responses. For example, one participant noted that he preferred the robot "Because it's easier to understand/hear a robot that corrects you". Other participants framed it as efficiency during problem solving: "If there's someone who can answer my questions out loud while I'm writing the code, I'd choose to use that (like a teacher) instead of going to the chat each time and explaining myself in writing – it's easier and faster", and "I find it much more comfortable to communicate verbally than to organize my thoughts in writing". Yet another participant referred to the intonation that cannot be expressed textually: "It's very convenient to talk to someone who listens and then provides you with a verbal and written explanation at the same time. The chat was nice, but I didn't feel like it recognized my tone of voice (it's in writing after all), which can be useful sometimes on assignments". It should be noted that the robot's and the chat's functionality was identical in terms of text processing and did not include the ability to recognize the participants' tone of voice.

(2) *A robot feels like someone is with you* – several participants highlighted the robot's social presence and the feeling of not being alone during programming: "The robot adds an experience to programming… the feeling that, as a student, I'm not alone". Another participant emphasized the physical, human-like partnership: "It's always more fun to work with someone who can talk and whom you can see physically, rather than alone or with a screen". Another participant referred to the robot as a personal teacher: "It feels like I'm talking to a real teacher who understands me and guides me in everything".

(3) *A robot can make you feel better* – participants connected the robot interaction to affective support, especially in relation to confidence and frustration regulation: "The feeling that… I'm not alone… raises my self-confidence". One participant described the robot's emotional sensitivity: "He is cute and manages to see that I am frustrated…". Others linked the robot's modality to a more comfortable experience: "Because talking with someone almost always gives a better feeling, and sometimes a spoken explanation is better".

5. Discussion

This pilot study aimed to examine whether delivering the same GenAI-based programming tutor through two modalities, a physically embodied social robot versus a screen-based chat interface, influences students' perceptions of the tutor's ToM including cognitive understanding and emotional awareness, as well as the tutor's perception of the student's cognitive and emotional state (RQ1), and students' technology acceptance, including perceived usefulness, perceived ease of use, and behavioral intention to use (RQ2). Overall, the preliminary results suggest that modality influenced ToM attributions, while its effects on technology acceptance were more selective.

The robot modality produced a consistent advantage across all ToM factors, with the largest differences emerging in the two factors that require awareness of the student's cognitive understanding and emotional state. A plausible interpretation is that physical embodiment increases the perceived social presence of the tutor, which in turn makes it easier for learners to infer that the tutor is "following" them, monitoring their progress, noticing confusion, and responding to frustration, rather than merely providing correct information. In this sense, embodiment may strengthen the impression that the tutor is a socially aware partner in the activity, not only an information source. Participants described the robot as easier to engage with verbally, as creating a sense that "someone is with you," and as supporting confidence and frustration regulation, each of which directly supports higher attributions of cognitive and emotional awareness. The strong robot advantage in ToM-related perceptions aligns with Theory of Mind as a framework for mental-state attribution [10], [20] and with research showing that people often respond socially to interactive technologies and infer "understanding" from behavioral cues [21]. Regarding TAM, the modality effect was limited. Even though some participants noted that it is easier to communicate verbally, overall participants rated both modalities as easy to use, possibly resulting in a ceiling effect. While the robot did not necessarily simplify the interaction, it appeared to enhance the learning experience. Specifically, participants described benefits such as speaking instead of typing, feeling accompanied, and receiving emotionally supportive feedback. These additional benefits likely contributed to the robot's higher ratings for perceived usefulness and behavioral intention to use. These results align with evidence from higher-education robotics suggesting that perceived usefulness can be a primary driver of intention to use, whereas ease of use may play an indirect or weaker role when baseline usability is high [18]. This is also consistent with emerging work on the acceptance of social robots as conversational interfaces for LLMs [19], in which social embodiment may enhance perceived value even when core functionality remains comparable.

5.1. Limitations, Future Directions

Several limitations should be noted. First, as a pilot study, the sample is small (N=14), which limits statistical power and the generalizability of effect estimates. Second, participants selected programming topics of varying difficulty and familiarity, introducing uncontrolled variability that may influence both perceived usefulness and the tendency to attribute understanding or emotional awareness. Third, the current evidence is primarily perception-based (TAM and ToM) - While these constructs are theoretically meaningful and strongly aligned with the qualitative themes, they do not yet establish learning gains or performance improvement.

Several alternative explanations should be considered. First, the robot advantage may partially reflect a novelty or halo effect, whereby an embodied system is judged as more socially capable simply because it is physically present and expressive. Second, demand characteristics (i.e., what participants thought were the research expectations) are possible. Participants may infer that the robot is the "special" condition and respond accordingly. Finally, it remains possible that some portion of the advantage is attributable to voice and multimodality rather than to embodiment per se. Future iterations could disentangle these mechanisms by adding conditions that isolate voice, for example, chat with high-quality text-to-speech.

5.2. Conclusions

The present results extend the literature by comparing a GenAI-based programming tutor with an embodied social robot to a chat-based tutor while holding the LLM's functionality constant across modalities. In this within-subject pilot, the robot version of the GenAI-based programming tutor was rated higher on all Theory of Mind factors, especially the tutor's perceived awareness of the student's cognitive and emotional state. Both modalities scored high on acceptance, but the robot was seen as more useful and elicited higher intention to use, with no ease-of-use difference. Qualitative themes echoed these advantages (verbal interaction, presence, support). Given that programming is cognitively demanding and often emotionally taxing [1], [2], a social robot may offer benefits beyond a screen-based tutor, especially through emotional support and a stronger sense of co-presence [8], [9], [17]. At the same time, this line of work also motivates caution: ToM attributions can be influenced by surface cues, and over-attribution raises ethical concerns about trust and perceived understanding [26].

Declaration on Generative AI

During the preparation of this work, the author used ChatGPT to correct grammar and spelling. After using these tools, the author reviewed and edited the content as needed, taking full responsibility for the publication's content.

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