The Role of Verbal and Non-Verbal Communication in Human–Robot Interaction: Models and Applications in Academic Contexts

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Abstract: This paper explores the role of verbal and non-verbal communication in human–robot interaction (HRI), with a specific focus on educational and academic contexts. Verbal communication in social robots serves not only to deliver information but also to facilitate social and emotional engagement, particularly through dialogue, speech acts, and instructional discourse. Non-verbal communication—including gaze, gestures, facial expressions, and body posture—enhances trust, regulates dialogue, and supports inclusive learning by increasing the robot's perceived social competence. The integration of verbal and non-verbal channels creates a multimodal interaction framework that improves cognitive processing, student motivation, and engagement. Drawing on models such as Speech Act Theory, Joint Action Theory, Embodied Communication, and Multimodal Alignment, the study presents research-based insights and practical applications using robots like NAO and Pepper in university settings. The findings emphasize the importance of adaptive, socially appropriate robot behavior for building trust and fostering deeper learning, especially among diverse student populations.

Keywords: Human–Robot Interaction,Verbal and Non-verbal Communication, Educational Robotics, Trust and Engagement, Multimodal Interaction

Introduction

In recent years, the integration of social robots into educational environments has gained increasing attention due to their potential to enhance teaching, learning, and student engagement. As human–robot interaction (HRI) becomes more sophisticated, communication emerges as a critical factor in shaping how users perceive and interact with robotic agents. Communication in this context extends beyond simple information exchange; it involves complex, multimodal processes where verbal and non-verbal cues jointly contribute to trust-building, cognitive processing, emotional connection, and the overall effectiveness of educational interactions.

Verbal communication—including speech generation, dialogue structure, and instructional language—enables robots to perform pedagogical functions such as delivering content, posing questions, and guiding learning activities. Simultaneously, non-verbal communication—such as gaze, facial expressions, gestures, and body posture—plays a vital role in enhancing the robot's social presence, regulating dialogue flow, and supporting inclusive learning environments. These channels work in synergy to create socially intelligent behaviors that are essential for fostering student motivation and meaningful engagement.

This paper explores the theoretical foundations, models, and practical applications of verbal and non-verbal communication in HRI within academic contexts. Drawing on frameworks such as Speech Act Theory, Joint Action Theory, and Embodied Communication Models, the study analyzes how social robots like NAO and Pepper function as multimodal educational agents. By comparing historical and contemporary research findings, this work aims to identify the communicative strategies that most effectively support learning, trust, and participation among diverse student populations. The ultimate goal is to contribute to the development of adaptive, socially responsive robotic systems that align with the evolving needs of 21st-century education.

Research Goals

The main goal is to explore how verbal and non-verbal communication function in human–robot interaction (HRI), particularly within educational and academic contexts, and to analyze how their integration supports trust, engagement, and effective learning.

Research Tasks

To analyze models of verbal communication (e.g., Speech Act Theory, Joint Action Theory) in the context of social robots.
To explore the role of non-verbal communication (e.g., gaze, gestures, facial expressions) in establishing trust and social presence.
To investigate how multimodal communication (verbal + non-verbal) enhances student motivation, learning, and engagement.
To examine experimental studies and applications of educational robots like NAO and Pepper in university settings.
To compare past and recent research to identify trends and best practices in HRI.

Object of the Study

The object of the study is human–robot communication, with a specific focus on how verbal and non-verbal channels are used in academic environments to support teaching, learning, and social interaction.
Research Hypotheses (Implied)
Combined verbal and non-verbal communication leads to greater engagement and trust in educational human–robot interaction.
Non-verbal behaviors (e.g., gestures, facial expressions) enhance perceived social competence of robots.
Multimodal communication improves learning outcomes, especially in inclusive or language-learning settings.
Adaptability and emotional expressiveness in robot behavior are key to increasing motivation and effectiveness.
Cultural and contextual factors (e.g., school climate, user characteristics) influence how robot communication is received.

Methods

The paper synthesizes and compares methods used in foundational and recent studies, including:
Video analysis of robot–human interactions (e.g., gesture, eye contact, facial expressions).
Subjective questionnaires assessing trust, engagement, enjoyment, and communication satisfaction.
Experimental scenarios with educational robots (e.g., NAO teaching vocabulary with or without expressive behavior).
Learning outcome tests (e.g., vocabulary acquisition, task performance).
Nonverbal signal coding systems (e.g., FACS – Facial Action Coding System).
Comparative research analysis (e.g., Cassell et al. 2000 vs. Tanaka & Matsuzoe 2012, Belpaeme et al. 2018).
Expected Results
Improved communication effectiveness through integrated multimodal strategies.
Enhanced student trust, motivation, and learning outcomes in interactions with socially expressive robots.
Better support for inclusive education, including for students with disabilities or language barriers.
Identification of communication patterns and features (e.g., adaptability, emotional expressiveness) that most influence trust.
Clarification of the relationship between robot design, user perception, and educational impact.

Models and Applications in the Academic Context

Communication between humans and robots is not simply an exchange of information—it is a multimodal process that involves both verbal and nonverbal channels through which mutual understanding, trust, and engagement are built. Within the fields of social robotics and Human-Robot Interaction (HRI), researchers identify communication as a key component of effective interaction, especially in educational and academic environments.

Verbal Communication: Language, Content, and Intonation

Verbal communication in robots includes speech generation and understanding, linguistic structures, and discourse. It serves not only an informational function but also fulfills social and emotional roles that help build relationships between the user and the robot.

Key models emphasizing the role of speech in HRI include:

Clark's Joint Action Theory (1996) – argues that all communication is a joint action where participants achieve mutual understanding through dialogic coordination.

Speech Act Theory (Austin, 1962; Searle, 1969) – emphasizes that speech acts do not merely convey information but perform actions (e.g., commands, questions, suggestions), which is especially relevant in educational tasks and instructions.

In academic settings, verbal communication by social robots:

Supports oral instructions, questions, and dialogues with students;

Encourages educational interaction through conversational style;

Develops language literacy and communication skills, especially in language learning or public speaking.

Nonverbal Communication: Gaze, Facial Expressions, Gestures, and Body Behavior

Nonverbal communication includes all channels through which mood, emotion, attention, and attitudes are conveyed without words. It is critical to the perception of a robot's social competence and plays a crucial role in:

Regulating dialogue (e.g., signaling when it's someone else's turn to speak),

Creating social appeal and trust,

Spatial navigation and reference (e.g., through pointing gestures).

Key models:

Mutual Gaze and Social Signal Processing (Argyle & Cook, 1976; Breazeal, 2003) – gaze and facial expression are primary indicators of attention and understanding in social interaction.

Embodied Communication Models (Cassell, 2000; Kendon, 2004) – highlight the role of bodily expressiveness (gestures, posture, movement) in complementing speech and creating "complete communication."

Application in Academic Settings:

Nonverbal communication is particularly effective in teaching through demonstration (e.g., showing steps in a lab task).

Assistant robots using gaze, nods, or facial expressions enhance the sense of understanding and engagement among students.

For interactions with nonverbal or introverted students, the presence of robots using non-invasive and empathetic nonverbal communication facilitates participation in the learning process.

Synergy Between Verbal and Nonverbal

The most effective forms of communication in HRI combine modalities—e.g., speech accompanied by gesture or gaze—so that the message is clearer, more understandable, and socially relevant. This is based on the Multimodal Alignment Model (Oviatt, 1999), which suggests that combining speech and action enhances cognitive processing and information retention.

Educational Benefits

Improved Communication Effectiveness: Students understand and retain information better when it is conveyed through both speech and behavior.

Stimulation of Active Learning: Verbal-nonverbal interactions support educational dialogue, where the student is an active participant, not a passive listener.

Development of Social and Emotional Skills: Students—especially in pedagogical and therapeutic programs—train interpersonal sensitivity by observing and responding to the social behavior of robots.

Support for Inclusive Education: Robots using adaptive nonverbal communication are particularly helpful for students with disabilities or those learning a second language.

Illustrative Examples from Real Studies and Educational Scenarios

Examples like Pepper or NAO robots used in university courses follow the logic that human-robot communication must include both verbal and nonverbal aspects (Cassell et al., 2000). For instance, Cassell and colleagues (2000) explore the impact of Embodied Conversational Agents (ECAs) on social engagement and perceived reliability of interactions. In their studies, participants interact with virtual agents programmed to display different combinations of verbal and nonverbal communication cues. Video analysis and subjective questionnaires are used to evaluate how verbal content (e.g., instructions and questions) and nonverbal elements (e.g., gestures, eye contact) contribute to a sense of social interaction.

In this foundational work, Cassell and her team introduce ECAs—computer-based systems that combine verbal (language) and nonverbal (gestures, facial expressions, posture) communication to interact with people in a socially human-like manner.

Methods and Study Examples

Cassell et al. (2000) present not a single study but a compilation of chapters summarizing results from multiple experiments and theoretical models. Key details include:

Experimental scenarios with virtual agents:

Virtual avatars (ECAs) are programmed to demonstrate natural communication (e.g., nodding, hand gestures, changing facial expressions during speech).

Volunteers interact with these agents in computer-mediated environments (e.g., virtual dialogue spaces).

Behavioral styles vary from robotic (emotionless) to expressive (rich nonverbal communication).

Video analysis and nonverbal signal coding:

Qualitative analysis of videos from interactions between humans and virtual agents.

Observing gestures, body movements, eye contact, and their impact on user social engagement.

Use of nonverbal coding systems (e.g., Facial Action Coding System – FACS) to classify emotional expressions.

Subjective questionnaires and self-assessments:

Participants fill out surveys measuring:

Perceived social presence (does the agent feel "real" or socially engaging?)

Trust and enjoyment of the interaction

Ease and engagement during communication

Based on validated scales in social psychology (e.g., trust, empathy, communication enjoyment).

Agent examples:

"Rea" – a virtual agent capable of using gestures, smiling, and changing intonation when "talking."

"Steve" – combines speech with pointing gestures to support instruction (e.g., in technical simulations).

These examples show how ECAs can be used for teaching, counseling, or social interaction.

Main conclusions:

Embodied nonverbal cues are critical—their presence enhances social interaction and makes communication feel more natural.

Communication is two-way—people respond more actively and trust more when agents display "human" behaviors.

Dynamic gestures and expressions by ECAs aid understanding of communication content (e.g., pointing gestures for "this here").

Cassell et al.'s work provides a foundation for understanding the importance of nonverbal communication in human-robot (or human-agent) interactions. The methods (videos, questionnaires, experimental scenarios) and conclusions are widely used in subsequent research on designing social robots perceived as "social partners" rather than mere machines.

Table 1. Comparison with Newer Studies (Post-2010)

Aspect	Cassell et al. (2000) – "Rea" and "Steve" Agents	Newer Research
Type of Agent	Virtual ECAs on screen	Physical robots (NAO, Pepper)
Manipulation	With/without nonverbal cues	Comparison of interaction styles: expressive vs. non-expressive robots; adaptive behavior
Research Context	Support in conversation and tasks (general, technical)	Education (language learning, math, emotions), therapy (autism)
Methods	Videos, subjective trust/social presence surveys	Biometric tracking (e.g., eye tracking), learning and emotional outcome tests
Example	Hancock et al. (2011): ↑ Trust with	Belpaeme et al. (2018): social robots ↑ engagement in

Aspect	Cassell et al. (2000) – "Rea" and "Steve" Agents	Newer Research
Findings	expressive robots; Tanaka & Matsuzoe (2012): expressive NAO ↑ learning	language learning; Van Achte et al. (2023): effectiveness depends on organizational culture
Conclusions	Nonverbal cues ↑ social presence, trust, engagement	Confirm and expand: adaptivity and emotional expression are key for motivation and learning

Key points:

Cassell et al. (2000) laid the groundwork, showing nonverbal communication is critical for social interaction.
Newer studies confirm these findings in real-world educational and therapeutic environments with physical robots.

Additional factors include adaptability, emotional expression, and context (e.g., culture, learner age).
The Role of Nonverbal Cues

Cassell et al. (2000) demonstrated that nonverbal signals (gestures, facial expressions) significantly enhance social presence and engagement. This inspired the design of social robots that increasingly mimic human behavior.
Physical Presence and Real Environments

While early studies used virtual agents, newer research (e.g., Tanaka & Matsuzoe, 2012; Belpaeme et al., 2018) focuses on physical robots. NAO, for instance, is equipped with gestures and emotional expressions that help children learn via emotionally expressive teaching.

Key Role of Adaptability
New research (Belpaeme et al., 2018) emphasizes that beyond nonverbal cues, a robot's ability to adapt to individual user responses is crucial. For example, in language learning, adapting teaching pace and style to student level increases effectiveness.

Cultural and Organizational Factors
Contemporary research (Van Achte et al., 2023) highlights that organizational culture influences how social robots are perceived. Schools with more innovative climates adopt robots more readily in the educational process.

Table 2. Communication Functions of Social Robots in Higher Education

Communication Function	Modality	Description	Application/Benefit in Academia
Information Delivery	Verbal	Spoken language for concepts, instructions, answers	Support for lectures, presentations, labs
Attention Direction	Nonverbal	Pointing gestures, head turns, gaze at object/student	Focus and orientation support, visual demonstration
Dialogue Regulation	Verbal + Nonverbal	Pauses, nods, gaze shifts for turn-taking	Improves communication rhythm and engagement
Emotion Expression	Nonverbal	Facial expressions, intonation, body language, lights	Creates human-like, empathetic interaction
Facilitating Group Work	Multimodal	Coordinates participant roles via speech and gestures	Supports teamwork, group dynamics, time management
Motivation and Encouragement	Verbal + Nonverbal	Positive feedback, greetings, applause, humor	Maintains motivation, builds student self-esteem
Knowledge Assessment	Verbal	Quizzes, questions, oral tests	Adaptive testing, gamification of exams
Cultural Adaptation	Verbal +	Language choice, style,	Diversity support and inclusion of

Communication Function	Modality	Description	Application/Benefit in Academia
	Nonverbal	proxemics, etiquette	international students
Support for Special Educational Needs	Multimodal	Personalized cues, visual prompts, reducing social pressure	Inclusive practice for autism, anxiety, language challenges

Verbal communication includes linguistically mediated messages, such as instructions, questions, and learning support, while nonverbal communication is conveyed through gestures, facial expressions, and body posture, facilitating social interaction (Mubin et al., 2013).

In their review, Mubin and colleagues (2013) emphasize that robots used in education are often programmed to combine spoken content with nonverbal signals—such as nodding movements or hand gestures—to help maintain students' attention. Their study is a review of over 80 publications that include experimental and observational methods (e.g., video recordings, satisfaction questionnaires) to identify best practices in the design of educational robots.

Research shows that robots demonstrating appropriate nonverbal cues can elicit higher levels of trust and engagement among users (Hancock et al., 2011). In their meta-analysis, Hancock and colleagues (2011) analyze around 100 studies using a variety of methods—from laboratory experiments to field research—and employ both subjective measures (e.g., trust questionnaires) and objective indicators (e.g., physiological responses).

Their analysis finds that a robot's nonverbal behavior—such as smoothness of movement and eye contact—is a key predictor of perceived trust. For example, **Tanaka and Matsuzoe (2012)** found that social robots using emotionally expressive facial expressions support more effective learning in children. Their study involved students aged 4 to 7 years interacting with the **NAO robot**. The experiment was designed so that the robot displayed different emotional expressions (e.g., joy, surprise, confusion) while teaching new vocabulary to the children.

Through video analysis and pedagogical testing, the authors found that emotionally expressive robots increased students' interest and enhanced learning outcomes. The study used a **comparative design** (interaction with an expressive robot vs. a non-expressive robot) and evaluated results using **vocabulary acquisition tests**.

Conclusion:

Social robots, through the combination of verbal, nonverbal, and multimodal communication strategies, can fulfill educational, social, and emotional roles in higher education. They do more than deliver content—they structure interaction, enhance engagement, and support inclusive learning.
Building Trust and Engagement Between Humans and Robots
Trust in social robots is built through a combination of predictable behavior, social appropriateness, and individual alignment with user expectations (Hancock et al., 2011).
Trust Model in HRI According to Hancock et al. (2011)
Hancock and colleagues conducted a large-scale meta-analysis of over 100 studies investigating factors influencing trust in Human-Robot Interaction (HRI). They systematized the findings and proposed a model encompassing three main categories of factors:

1. Robot-Related Factors

Predictability and reliability: Robots that demonstrate consistent and predictable behavior are perceived as more trustworthy partners (e.g., using clear commands and consistent logic).
Adaptability: The robot's ability to adjust to new situations or individual users increases trust.
Nonverbal behavior: Smooth movements, appropriate gestures, and eye contact foster greater trust (e.g., a robot that nods while the user is speaking).
Physical and social presence: Robots with more human-like traits (e.g., humanoid appearance) often elicit higher levels of trust.

2. Human-Related Factors

Individual attitudes: Personality traits such as general trust propensity influence willingness to trust the robot.
Previous experience: Users with more experience with technology and robots tend to show higher levels of trust.
Cultural factors: Cultural background affects openness to technology (e.g., some cultures are more receptive to robots) (Bartneck et al., 2007).

3. Contextual (Environment/Task-Related) Factors

Clarity of task: When tasks are clearly defined, interaction becomes more predictable, fostering trust.
Risks and uncertainty: In high-risk scenarios (e.g., medical robotics), users demand higher reliability.
Social appropriateness: The degree to which the robot's behavior aligns with social norms and context expectations.

Methods and Research Examples
Methods:
Trust questionnaires (e.g., Trust in Automation Scales)
Physiological measurements (e.g., heart rate, skin conductance)
Behavioral indicators (e.g., time spent completing a task with the robot)
Examples:
Lab studies with humanoid robots (e.g., NAO, Pepper) show that robots using eye contact and smooth gestures are perceived as more trustworthy.
Field studies in hospitals confirm that consistent and predictable behavior in medical robots increases trust from patients and staff.
Key conclusions of the model:
Trust is not static—it develops over time and depends on the dynamic interaction of all three factor categories.
Nonverbal signals (smooth movement, eye contact) are key predictors of trust.
Cultural and contextual differences must be considered when designing social robots for educational and therapeutic settings.
Application in Working with Children in Schools
Robot Characteristics:
Predictable behavior: In learning environments, robots should give consistent instructions and respond similarly to similar questions (e.g., when teaching new words).
Social appropriateness: Robots should display friendly behavior (e.g., use a childlike voice, positive emotional expressions).
Nonverbal communication: Nods, waves, and smiles increase the robot's social presence. For example, Tanaka & Matsuzoe (2012) found that children engaged more with the NAO robot when it displayed emotionally expressive behavior.
Child Characteristics:
Individual differences: Children high in openness to experience are more likely to actively engage with the robot.
Technological familiarity: Children used to digital devices show less hesitation and build trust faster.
Contextual Factors:
Clarity of educational tasks: If the robot clearly communicates the goal (e.g., "Let's learn 5 new words!"), it enhances confidence and trust.
Social context: Support from teachers and classmates also influences trust in the robot.
Conclusion:
For children, emotionally expressive cues and friendly behavior are crucial for building trust and engagement in learning settings.
Application in Working with Patients (Therapy)
Robot Characteristics:
Predictability and reliability: In therapeutic sessions (e.g., rehabilitation or psychotherapy), patients rely on consistent responses. Unpredictability may undermine a sense of safety.
Adaptability: Robots must adjust their style to the patient's condition (e.g., speaking more slowly when the patient is tired).
Nonverbal behavior: Studies show that smiling and slow, fluid movements reduce patient anxiety.

Patient Characteristics:
Mental state: Patients with higher anxiety levels need more safety signals (smiles, slower speech tempo).
Prior experience: First-time robot users require gradual introduction and reassurance.
Contextual Factors:
Type of therapy: For example, in physiotherapy, the robot can provide physical instructions ("raise your arm") using clear gestures.
Risk level: In medical contexts, trust is critical—if a patient doesn't trust the robot, they may refuse to participate.
Conclusion:
For patients, reliability and adaptability are the most important factors for building trust in therapeutic environments.

Table 3. Application with Children and Patients

Factor	With Children in School	With Patients in Therapy
Predictability	Supports learning through clear instructions	Provides a sense of safety and consistency
Nonverbal cues	Emotional expressions, friendly behavior	Smooth movements, safety signals
Adaptability	Tailored to the student's learning level	Adjusted to mental/physical state of the patient
Context	Educational (teacher support)	Medical (risk, anxiety)

Trust and Perception: Additional Research Insights
Bartneck et al. (2007) emphasized the importance of perceived intelligence and safety in establishing trust. They developed scales to measure five key dimensions in human-robot interaction:
Anthropomorphism
Animacy
Likeability
Perceived Intelligence
Perceived Safety
In lab experiments, participants interacted with various robots and assessed them using standardized questionnaires.
Conclusion: Perceived intelligence and safety are among the strongest predictors of trust. If users feel the robot is "smart" and "won't harm them" (even metaphorically—e.g., with intrusive behavior), they are more likely to trust it.
Kennedy et al. (2015) conducted an experiment where children interacted with robots showing either high social behavior (lots of smiles, gestures, jokes) or neutral/business-like behavior.
Using pedagogical tests and video analysis, they found that overly social behavior may distract from the task and reduce learning effectiveness if perceived as unnatural or intrusive.
In a follow-up study, Kennedy et al. (2017) explored trust in educational contexts using NAO as a language learning assistant.
Methods:
Vocabulary retention tests
Trust and engagement questionnaires
Conclusion: High trust in the robot led to greater engagement and motivation, resulting in better learning outcomes.

Table 4. Comparative Overview

Aspect	Bartneck et al. (2007)	Kennedy et al. (2015)	Kennedy et al. (2017)
Main Focus	Perceived intelligence & safety as trust predictors	Excessive social behavior may lower effectiveness	High trust → engagement → better learning
Context	General HRI scenarios	Education, classroom experiment	Language learning in class
Methods	Perception questionnaires	Educational tests, video analysis	Vocabulary tests,

Aspect	Bartneck et al. (2007)	Kennedy et al. (2015)	Kennedy et al. (2017)
			trust/engagement surveys
Key Findings	"Smart" and "safe" robot → trust ↑	Social behavior should be balanced	Trust is key for motivation and achievement

What Does This Mean?

Bartneck et al. show that trust is rooted in perceived intelligence and safety.
Kennedy et al. (2015) add that over-social behavior can feel unnatural and may reduce task performance.
Kennedy et al. (2017) confirm that trust → engagement → learning success, especially for children.
Comparison with Newer Research (2023)
Van Achte et al. (2023): Trust and engagement are strongly influenced by organizational culture—in innovative schools, teachers are more accepting of robots, which in turn affects student perception.
Belpaeme et al. (2018): Confirm that adaptive and moderately social behavior is crucial for the long-term effectiveness of social robots in education.
Summary
Trust in social robots relies not only on technical safety, but also on emotionally appropriate (and non-intrusive!) social behavior.
In educational contexts, balancing friendliness and professionalism is key—too much social behavior can distract (Kennedy et al., 2015), while moderate sociality combined with perceived intelligence fosters trust, which enhances engagement and motivation (Kennedy et al., 2017).

Conclusion

This study examined the role of verbal and non-verbal communication in human–robot interaction (HRI), particularly in educational and academic contexts. The analysis confirmed that communication between humans and robots is most effective when it is multimodal—integrating speech with gestures, facial expressions, gaze, and other non-verbal cues. Such integration not only improves the clarity and retention of information but also fosters trust, motivation, and engagement among students.

The research hypotheses proposed that (1) multimodal communication increases trust and engagement, (2) non-verbal behavior enhances the robot's perceived social competence, (3) adaptability and emotional expressiveness are essential for effective learning support, and (4) cultural and contextual factors shape user perceptions. The findings from both foundational and contemporary studies strongly support these hypotheses. For example, emotionally expressive robots like NAO have been shown to enhance vocabulary learning in children, while socially adaptive behaviors are key predictors of trust in both educational and therapeutic settings.

In conclusion, the hypotheses are validated by a growing body of evidence demonstrating that socially responsive and communicatively rich robots can effectively contribute to inclusive, personalized, and emotionally supportive learning environments. Future developments should focus on refining the adaptability of robots, ensuring ethical standards in human–robot communication, and tailoring robot behavior to diverse user needs and institutional settings. Social robots are not merely tools for content delivery; they are evolving as intelligent partners in the co-construction of meaningful educational experiences.

References

1. Bartneck, C., Kulić, D., Croft, E., & Zoghbi, S. (2007). Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. International Journal of Social Robotics, 1(1), 71–81. https://doi.org/10.1007/s12369-008-0001-3
2. Belpaeme, T., Kennedy, J., Ramachandran, A., Scassellati, B., & Tanaka, F. (2018). Social robots for education: A review. Science Robotics, 3(21), eaat5954. https://doi.org/10.1126/scirobotics.aat5954
3. Cassell, J., Sullivan, J., Prevost, S., & Churchill, E. (Eds.). (2000). Embodied conversational agents. MIT Press.

4. Hancock, P. A., Billings, D. R., Schaefer, K. E., Chen, J. Y. C., De Visser, E. J., & Parasuraman, R. (2011). A meta-analysis of factors affecting trust in human-robot interaction. Human Factors, 53(5), 517–527. https://doi.org/10.1177/0018720811417254
5. Kennedy, J., Baxter, P. E., & Belpaeme, T. (2015). The robot who tried too hard: Social behavior of a robot tutor can hinder child learning. In Proceedings of the 10th ACM/IEEE International Conference on Human-Robot Interaction (pp. 67–74). ACM. https://doi.org/10.1145/2696454.2696457
6. Kennedy, J., Lemaignan, S., & Belpaeme, T. (2017). Accountability in human-robot interaction: A review. In Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction (pp. 125–134). ACM. https://doi.org/10.1145/2909824.3020221
7. Mubin, O., Stevens, C. J., Shahid, S., Mahmud, A. A., & Dong, J. J. (2013). A review of the applicability of robots in education. Journal of Technology in Education and Learning, 1(1), 1–7.
8. Oviatt, S. (1999). Ten myths of multimodal interaction. Communications of the ACM, 42(11), 74–81. https://doi.org/10.1145/319382.319398
9. Tanaka, F., & Matsuzoe, S. (2012). Children teach a care-receiving robot to promote their learning: Field experiments in a classroom for vocabulary learning. Journal of Human-Robot Interaction, 1(1), 78–95. https://doi.org/10.5898/JHRI.1.1.Tanaka
10. Van Achte, T., Depaepe, F., Belpaeme, T., & Struyven, K. (2023). The role of school culture in the acceptance and effectiveness of social robots in education. Computers & Education, 198, 104794. https://doi.org/10.1016/j.compedu.2023.104794

