Chapter 10
Social Robots in Education: Conceptual Overview and Case Study of Use

Josef Guggemos, Sabine Seufert, Stefan Sonderegger, and Michael Burkhard

10.1 Introduction

Social robots could become an essential part of the educational infrastructure (Belpaeme, Kennedy, Ramachandran, Scassellati, & Tanaka, 2018; Cheng, Sun, & Chen, 2018; Papadopoulos et al., 2020). A social robot can be defined as "an autonomous or semi-autonomous robot that interacts and communicates with humans by following the behavioral norms expected by the people with whom the robot is intended to interact" (Bartneck & Forlizzi, 2004, p. 592). The quasi-standard robot in educational settings is currently Nao (see Fig. 10.1), developed by SoftBank Robotics (Belpaeme et al., 2018). In recent years, Pepper (Fig. 10.1), also a humanoid robot from SoftBank Robotics, has been increasingly used (Woo, LeTendre, Pham-Shouse, & Xiong, 2021).

Social robots can be used to teach about robots or as teaching aids (Guggemos & Seufert, 2021; Mubin, Stevens, Shahid, Mahmud, & Dong, 2013). When teaching about social robots, they are the actual content of instruction, for example, to teach computational thinking (Ching, Hsu, & Baldwin, 2018; Guggemos, 2021), or they are used to evoke interest in technology. This latter kind of use will not be a part of this chapter. Rather, how social robots (in collaboration with teachers) can carry out selected duties in the classroom will be addressed. In this vein, frequently mentioned roles are (Belpaeme et al., 2018; Mubin et al., 2013; Woo et al., 2021) teaching assistant, tutor, and peer. Social robots as teaching assistants have gained much attention, especially in language learning (van den Berghe, Verhagen, Oudgenoeg-Paz, van der Ven, & Leseman, 2019). For instance, Alemi, Meghdari, and Ghazisaedy

J. Guggemos (✉) · S. Seufert · S. Sonderegger · M. Burkhard
Institute for Educational Management and Technologies, University of St. Gallen, St. Gallen, Switzerland
e-mail: josef.guggemos@unisg.ch

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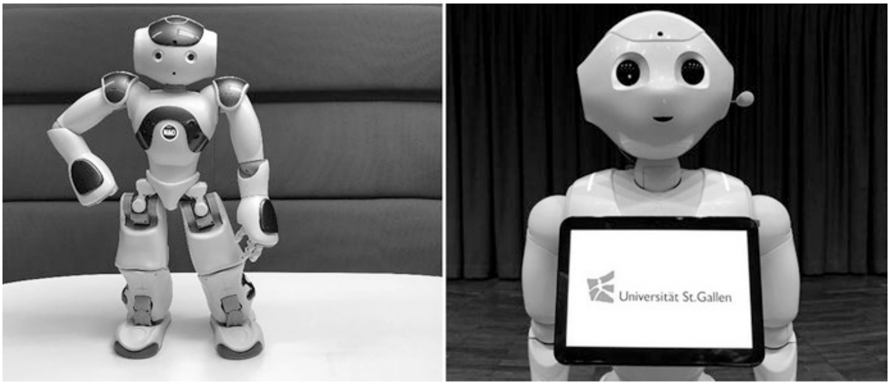

Fig. 10.1 On the left, the social robot Nao (height = 58 cm); on the right, Pepper (height = 120 cm)

(2015) used Nao as a teaching assistant for English as a foreign language among 12–13-year-olds. Nao played games with students, called them out, performed songs, positively reinforced correct answers, and made mistakes on purpose. Nao has also been successfully used to assist teachers in storytelling for kindergarten children (Conti, Cirasa, Di Nuovo, & Di Nuovo, 2020). Besides assisting the teacher, social robots can also act as tutors or peers. The role of a peer might have the advantage that students are more willing to accept mistakes from a peer in comparison to a tutor (Baxter, Ashurst, Read, Kennedy, & Belpaeme, 2017). In a long-term experimental study, Vogt et al. (2019) used Nao as an English foreign language tutor with 6-year-old children. The children played educational games on a tablet; Nao provided verbal support in the form of instructions, translations, and feedback and nonverbal support in the form of gestures. Concerning social robots as peers, Jamet, Masson, Jacquet, Stilgenbauer, and Baratgin (2018) reported on the overall positive effects of a learning by teaching approach, based on a review of the literature. Hood, Lemaignan, and Dillenbourg (2015), for example, asked 7–8-year-olds to teach a Nao robot handwriting: the robot writes a letter and asks for feedback; the child provides feedback via demonstration using a digital pen and a tablet; the robot responds to the feedback until the child is satisfied with the robot's performance.

Overall, social robots show promising results in terms of cognitive and affective learning outcomes (Belpaeme et al., 2018). However, a physical presence is not imperative for social agents because they do not have to carry out physical tasks, like industrial robots. Hence, social agents could also appear virtually on a screen as a telepresence robot or as a virtual agent (Li, 2015). Since physical presence incurs additional cost, including servicing and transporting the robot to the venue, this type of usage has to be justified (Belpaeme et al., 2018). The literature review of Li (2015) concludes that people respond more favorably to physical robots in comparison to virtually present robots. In light of this, social robots may actually have an added value in comparison to virtual agents, due to their physical presence.

This chapter aims at shedding light on the phenomenon of social robots in education. To this end, Section 10.2 characterizes social robots by means of visual appearance and social capabilities, as well as autonomy and intelligence. Section 10.3 describes how scenarios for the use of social robots can be identified, including ethical questions that need to be addressed and how technology acceptance of such robots can be evaluated. Section 10.4 explains how Lexi, a Pepper-model type, was used as a teaching assistant on an academic writing course and reports findings from this project. Section 10.5 outlines the conclusions and provides avenues for further research.

10.2 Characteristics of Social Robots

Three characteristics may be useful to describe social robots (Baraka, Alves-Oliveira, & Ribeiro, 2020): visual appearance, social capabilities, and autonomy and intelligence.

10.2.1 Visual Appearance

In education, bio-inspired social robots—humanoid and zoomorphic—seem to be prevalent (Baraka et al., 2020). Figure 10.2 shows various types of regularly used robots, beyond Nao and Pepper (Fig. 10.1). Humanoid robots resemble the human body in varying degrees. Androids, a subset of humanoid robots, are designed to be highly anthropomorphic. A special type of android is a geminoid, which duplicates an existing person (Nishio, Ishiguro, & Hagit, 2007). The relationship between humanlike appearance and human affinity toward social robots may not be linear. Rather, Mori posited the idea of an "uncanny valley" (Mori, MacDorman, & Kageki, 2012): human affinity toward social robots increases with humanlike appearance until the uncanny valley is reached whereby people experience an eerie sensation. In 48% of the studies reviewed by Belpaeme et al. (2018), a Nao model is used; further humanoid robots are Wakamaru (5%), Robovie (4%), and Bandit (4%). Animal-shaped social robots can fall into two categories (Baraka et al., 2020):

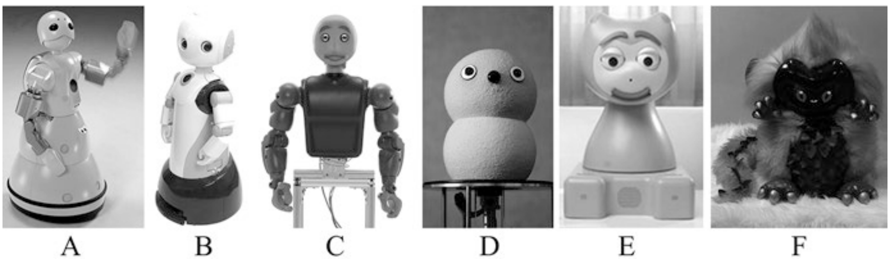

Fig. 10.2 Examples of social robots in education: (**a**) Wakamaru, (**b**) Robovie, (**c**) Bandit, (**d**) Keepon, (**e**) iCat, and (**f**) DragonBot

familiar versus unfamiliar and real as opposed to imaginary. The iCat (4%) resembles a cat and is an example of a real and familiar animal. The DragonBot (4%) is an example of a familiar imaginary animal, and the Keepon (6%) an example of an unfamiliar imaginary animal. These percentages also refer to the studies reviewed by Belpaeme et al. (2018).

Evidence is available concerning the influence of the robot's visual appearance on desired outcomes (see also Sect. 10.4). The literature review of Mou, Shi, Shen, and Xu (2020) demonstrated a substantial influence of visual appearance on perceived robot personality. Interestingly, humanoid robots may not necessarily be superior to animal-shaped robots: people may form unrealistic expectations that cannot be met at the current technological state of the art and are eventually disappointed (Henschel, Laban, & Cross, 2021). In the context of education, however, studies that compare different types of robots in the same setting are scarce (Belpaeme et al., 2018).

10.2.2 Social Capabilities

Social capabilities address the ways in which social robots engage in interactions with humans. An important aspect is verbal and nonverbal communication (Mavridis, 2015). Social robots can communicate using a combination of natural speech, motion, lights, and sounds (Baraka et al., 2020). As can be seen from Figs. 10.1 and 10.2, all types of robots have eyes. Gaze is a crucial element in nonverbal communication (Admoni & Scassellati, 2017), and eye contact is important in social encounters (Ahmad, Mubin, & Orlando, 2017). Niculescu, van Dijk, Nijholt, Li, and See (2013) provided evidence for the importance of voice characteristics and language cues for the perceived quality of interaction with the robot. Salem, Kopp, Wachsmuth, Rohlfing, and Joublin (2012) described the positive influence of social robot gestures on its evaluation by users. All these features seem to influence the perceived robot personality (Mou et al., 2020), which can positively impact the willingness to interact with a robot (Fong, Nourbakhsh, & Dautenhahn, 2003).

Empathy might be a social capability of specific importance in human-robot interaction (Baraka et al., 2020). Leite, Castellano, Pereira, Martinho, and Paiva (2014, pp. 330–331) presented a model demonstrating how social robots can show empathy. First, the affective state of the user is identified using visual and acoustical cues, as well as information about the current situation. Identified emotions could be anger, contempt, disgust, fear, happiness, neutral, sadness, and surprise. Moreover, the situation could offer information. For instance, if a student has just received inconvenient feedback, negative emotions may be likely. Second, based on the user's current affective state, the robot generates an empathic response, for example, an appropriate facial expression. Third, if the affective state is negative, the robot takes action to reduce the distress of the user. To this end, it shows supportive behaviors: "information support" (advice or guidance), "tangible assistance" (concrete support, e.g., by providing services), "esteem support" (reinforcing the user's sense of competence), and "emotional support" (an expression of caring or connectedness). Fourth, since remembering past interactions is crucial for building relationships, the robot utilizes information from previous interactions with the user to generate a dialogue that aims to give the user the feeling of "being cared for."

10.2.3 Autonomy and Intelligence

10.2.3.1 Autonomy

Autonomy can be defined as "the extent to which a robot can **sense** its environment, **plan** based on that environment, and **act** upon that environment with the intent of reaching some **task-specific goal** (either given to or created by the robot) without external **control**" (Beer, Fisk, & Rogers, 2014, p. 77). Table 10.1 presents a taxonomy that outlines the autonomy continuum, ranging from fully teleoperated to fully autonomous, depending on the level of human intervention. According to the definition of autonomy, it can be characterized by the involvement of the robot in sensing, planning, and acting. However, this taxonomy of social robot autonomy neither implies that full autonomy in educational settings is possible at the current technological state of the art nor that it is desirable. Rather, the level of autonomy should be a design choice (Baraka et al., 2020). It may be helpful in the design process of cases of use as the taxonomy can split up tasks and assign (sub-)tasks to either the robot or the teacher. Table 10.1 depicts the continuum of robot autonomy and illustrates it using the example of classroom management.

At the current technological state of the art, autonomy—even at a low level—is hard to achieve. Woo et al. (2021) reviewed studies in naturalistic classroom settings ("in the wild"). They found that in only 23 out of 126 studies (18%) the robot acted autonomously, at least to some degree.

For research purposes, the Wizard of Oz technique has regularly been used; in other words, this involves "a person (usually the experimenter, or a confederate) remotely operating a robot, controlling any of a number of things, such as its movement, navigation, speech, gestures, etc." (Riek, 2012, p. 119). By means of this, a desired level of autonomy can be simulated. Guidelines on how to conduct studies using the Wizard of Oz technique are available (Riek, 2012).

10.2.3.2 Intelligence

Educational situations are characterized by a high degree of complexity and events that are difficult to predict. Hence, intelligence is necessary in order to achieve robot autonomy. Intelligence can be regarded as the "capacity of an information-processing system to adapt to its environment while operating with insufficient knowledge and resources" (Wang, 2019, p. 17). In line with the definition of

Table 10.1 Social robot autonomy in education

Level of autonomy	Description	Example from classroom management
(Assisted) teleoperation	"The robot assists the human with action implementation. However, sensing and planning is allocated to the human"	The teacher monitors the classroom to detect undesired behavior, decides that an intervention is necessary for a specific student, and prompts the robot to call the student to order
Batch processing	"Both the human and robot monitor and sense the environment. The human, however, determines the goals and plans of the task. The robot then implements the task"	Teacher and robot monitor the classroom to detect undesired behavior. The teacher utilizes the information provided by the robot to decide what to do and prompts the robot to carry out this action
Decision support	"Both the human and robot sense the environment and generate a task plan. However, the human chooses the task plan and commands the robot to implement actions"	Teacher and robot monitor the classroom to detect undesired behavior. The robot suggests potential actions. The teacher decides on the action to be carried out and prompts the robot to do so
Shared control with human initiative	"The robot autonomously senses the environment, develops plans and goals, and implements actions. However, the human monitors the robot's progress and may intervene and influence the robot with new goals and plans if the robot is having difficulty"	The robot monitors the classroom to detect undesired behavior, decides on adequate means, and carries them out. The teacher monitors the robot and provides corrective feedback to the robot
Shared control with robot initiative	"The robot performs all aspects of the task (sense, plan, act). If the robot encounters difficulty, it can prompt the human for assistance in setting new goals and plans"	The robot monitors the classroom to detect undesired behavior, decides on adequate means, and carries them out. The robot asks the teacher for help if necessary, e.g., if the classification probability does not meet a desired level
Executive control	"The human may give an abstract high-level goal […]. The robot autonomously senses environment, sets the plan, and implements action"	The teacher sets the high-level goal, e.g., optimal classroom management, and the robot uses its capabilities to carry out this complex task
Supervisory control	"The robot performs all aspects of the task, but the human continuously monitors the robot, environment, and task. The human has override capability and may set a new goal and plan"	The robot carries out all classroom management activities. During this process, the teacher might prompt the robot to act less harshly
Full autonomy	"The robot performs all aspects of a task autonomously without human intervention in sensing, planning, or implementing action"	The robot carries out all classroom management activities without any intervention from the teacher

Note: Levels of autonomy and description taken from Beer et al. (2014, p. 87) autonomy, sensing, planning, and action have to be considered. To sense the environment, social robots can rely on cameras, microphones, and bumpers, as well as tactile, 3D, sonar, and laser sensors (Pandey & Gelin, 2018). By means of speech-to-text engines, transcripts of verbal input can be obtained for further analysis. In the next step, the obtained data has to be interpreted; for example, an answer to a question needs to be classified as incorrect, or the student has to be assigned a value for happiness based on a taken picture. In the planning phase, the robot decides what action should be carried out based on the specified goals, possible actions, and available information. The available information from the robot's sensors can be complemented with further data, for example, from the learning management platform. Moreover, the robot can access information about social expectation concerning appropriate robot behavior, such as how to show empathy. Based on these elements, the robot decides what action contributes most to achieving the specified goal. Afterward, the robot carries out the selected action. This includes verbal and nonverbal reactions, for example, positive encouragement and corrective feedback via gestures, body movement, speech, light, and sound.

The robot does not have to perform the above-described processes solely by relying on its hard- and software. Rather, it can access (artificial intelligence based) remote services via WiFi and using API services. An example is emotion and sentiment analysis (see Khanal, Barroso, Lopes, Sampaio, & Filipe, 2018). Chatbots such as Jill Watson can be used to answer student questions (Goel & Polepeddi, 2016). Furthermore, if the robot should be a tutor, an intelligent tutoring system (Mousavinasab et al., 2021) could act as the basis. In this vein, it may also be beneficial for the robot to have access to an available learning analytics system (Ifenthaler, 2015).

Due to the complexity of natural classroom settings, it is important for the robot to have learning capabilities in order to improve its performance. This can be achieved by means of machine-learning methods (Mosavi & Varkonyi-Koczy, 2016). For instance, the robot can use feedback from the teacher to improve its performance of subsequent tasks (reinforcement learning: Mosavi & Varkonyi-Koczy, 2016).

10.3 Use of Social Robots

10.3.1 Task Analysis

Beer et al. (2014) argue that the level of robot autonomy is a design choice. The starting point for determining suitable levels of autonomy and identifying corresponding use scenarios may be tasks carried out by teachers. In the educational context, teaching standards (e.g., InTASC Model Core Teaching Standards; CCSSO, 2021) could be used to identify the tasks of teachers. Moreover, characteristics of high-quality learning environments could be revealing (Bransford, Brown, &

Cocking, 2000). According to Praetorius, Klieme, Herbert, and Pinger (2018), the basic characteristics of high-quality teaching are classroom management, student support, and cognitive activation. *Classroom management* addresses the fostering of desirable student behaviors while at the same time preventing undesirable ones. Examples of the former are clear rules and routines. *Student support* draws from the self-determination theory and aims at supporting experiences of competence, autonomy, and social relatedness. *Cognitive activation* deals with the involvement of students in higher-level thinking, for example, by offering tasks of suitable difficulty (Kärner, Warwas, Krannich, & Weichsler, 2021). These findings seem to be well in line with the role of social robots as teaching assistants and tutors. Overall, it might be important to start from a sound conceptual basis of how people learn and what constitutes high-quality instruction. This could prevent the development and use of such AI-based technology as an end in itself (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019).

Not all teaching tasks are suitable to be performed by social robots, especially those which are critical or too complex. Critical tasks include those that have serious consequences if carried out inappropriately, for example, determining which students have to repeat the class. Ethical concerns or a lack of technology acceptance (see Sect. 3.3) could also constitute critical tasks. In terms of complexity, studies about autonomous robots reveal drivers (Woo et al., 2021). Social robots are generally used in a one-to-one or one-to-a-class setting. The robot does not have to navigate the classroom to approach individual students or teams, which is a highly complex task for a robot due to the changing environment. Moreover, a conversation within a group in a noisy environment, as can be characteristic for group work in naturalistic classrooms, causes high complexity. Besides this, the instructional content becomes increasingly complex: tutoring on the elementary level, for example, in vocabulary learning, is less complex in comparison to the university level (Handke, 2020).

However, even for complex tasks, a social robot can take over sub-tasks, for example, monitoring the classroom as part of the overall task "classroom management" (see Table 10.1). The ways in which teacher and social robot can collaborate will be outlined in the next section.

10.3.2 Task Sharing of Human and Robot

Following a symbiotic design approach, as outlined by Baraka et al. (2020, pp. 51–53), social robots and humans could collaborate in ways that benefit both parties. This is in line with the concept of hybrid intelligence (Dellermann, Ebel, Söllner, & Leimeister, 2019). Humans and smart machines have complementary capabilities that augment each other. Human strengths comprise flexibility and transfer, real empathy and creativity, annotation of arbitrary data, and common sense. Smart machines have strengths in pattern recognition, dealing with probabilities, and ensuring consistency and speed, as well as efficiency. For instance, in order to cognitively activate students, considering prior knowledge is important in order to offer a task of suitable difficulty (Sweller, 2020). The social robot could quickly make a suggestion for a suitable task based on the previous achievements of the student and their current emotional state. For the teacher, it would not be possible to access and process all the available information in a classroom setting. However, the teacher should not blindly trust in the suggestions of the robot, but critically question its decisions and actions (Dellermann et al., 2019). Eventually, the teacher could make the decision what task should be assigned to the student, also based on intuition. This final decision might be better in comparison to the decision of either the social robot or the human teacher in isolation. Furthermore, the teacher may train the social robot to improve the precision of its future predictions. For instance, the teacher can label predictions as wrong and therefore help the robot to improve its performance. Moreover, the teacher may help the robot to overcome physical obstacles and therefore reduce environmental complexity for the robot (Baraka et al., 2020). Conversely, the teacher might benefit from the social robot's feedback concerning their performance in the classroom.

The leading question to consider, however, may be: how can the teacher and social robot, as a team, best perform the tasks that are necessary to ensure a high-quality learning environment? With this in mind, Burkhard, Seufert, and Guggemos (2021a, 2021b) argue for focusing on the comparative advantages of both parties. Although a symbiotic design approach seems promising, from a conceptual point of view, teamwork with smart machines, such as social robots, is a complex endeavor and a novel research field with many open-ended questions (Seeber et al., 2020).

10.3.3 Restrictions of Social Robot Use

10.3.3.1 Ethical Aspects

Adherence to ethical standards may be necessary in order to maintain the moral legitimacy of the organization (Suchman, 1995). Sharkey (2016) and Serholt et al. (2017) discussed the ethical concerns of social robots in classrooms. Privacy is mentioned as an important aspect. To act (in part) autonomously, robots continuously evaluate their environment and collect data about students, for example, their emotional state. Privacy issues may include "amount of data; sensitivity of data; security risks such as hacking; cloud connectivity; third-party access" (Lutz, Schöttler, & Hoffmann, 2019, p. 424). A strategy has to be developed concerning how to deal with these issues. It may include transparency, student control over data, and right of access, as well as accountability and assessment (Pardo & Siemens, 2014).

Other ethical concerns are the undesired consequences of student-robot interaction. Excessive use of the robot may impede the development of social skills among students. For instance, students may form unrealistic expectations about social interactions due to the high adaptiveness and predictability of social robots; this might especially be a concern among young children (Sharkey, 2016). Moreover, it is questionable to what extent a robot should be allowed to exert power over students. Taking the example of classroom management, the robot could only be allowed to positively encourage students rather than penalize them. Furthermore, students may not always act benevolently toward robots. Brščić, Kidokoro, Suehiro, and Kanda (2015) reported abusive behavior of children, for example, punching, toward social robots operating in public places. Although such behavior may be unlikely when teachers are present, an interesting question that arises might be how will the robot be allowed to defend itself?

The role of teachers is a further ethical consideration. Concerns about the replacement of teachers by smart machines may be unfounded (Belpaeme & Tanaka, 2021; Frey & Osborne, 2017). Nevertheless, teachers need to be reassured that the intention is not to replace them by social robots (Mubin et al., 2013). Although teachers are unlikely to be replaced by smart machines, the teacher role is likely to change if teachers are expected to collaborate with social robots. Not all teachers may appreciate this new role or the input provided by the robot, for example, feedback about their own performance. Moreover, as resources are scarce, allocating more funds to social robots could indirectly affect teachers, as budgets for both them and their training might be cut.

Physical harm caused by social robots is unlikely due to various safety measures (Pandey & Gelin, 2018). However, as the robot itself cannot be held responsible, the question arises who should be held accountable for the robot's actions. If teachers should be made responsible, it needs to be clarified how they can be involved in the process of sensing, planning, and acting in order to be able to take over responsibility. However, insights into these processes may be difficult to ascertain because AI systems are often a black box. Developments in the research field of explainable AI may help to alleviate this problem (Gunning et al., 2019).

As detailed in Sect. 2.3, learning capabilities are necessary for social robots. Training opportunities in naturalistic settings are vital in order to allow the robot to learn from mistakes; not all potential circumstances can be anticipated in simulations or laboratory settings. However, to fine-tune the robot in naturalistic settings may only be acceptable if the error rates in controlled settings are markedly lower for the robot in comparison to a teacher (Vallor & Bekey, 2017). Moreover, human-generated learning data may be biased concerning, for example, gender, socioeconomic status, and migration background (Vallor & Bekey, 2017). This could reinforce prejudices because robots might be deemed to act objectively. To tackle the issue of biases in AI applications, the concept of "fair AI" may be promising (Feuerriegel, Dolata, & Schwabe, 2020).

10.3.3.2 Technology Acceptance

Eventually, over time, social robots may have to be used by both teachers and students. If teachers and students were reluctant to use social robots (in specific areas), then robots would not be useful, regardless of their actual potential value. Several frameworks are available for evaluating the acceptance of intelligent agents in education (Sohn & Kwon, 2020). Regularly used frameworks in the context of social robotics are the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) (Fridin & Belokopytov, 2014). These models are informed by the theory of planned behavior (Scherer, Siddiq, & Tondeur, 2019). In line with this theory, predictors of the intention to use social robots are attitudes toward their specific use, subjective norms, and perceived behavioral control (Ajzen, 1991).

Social robot acceptance studies usually enrich generic technology acceptance models with characteristics of the robot, for example, the appearance or the interaction experience, such as privacy concerns. A prominent example is the study of Heerink, Kröse, Evers, and Wielinga (2010) that evaluated the acceptance of the iCat (see Fig. 10.2) by elderly users. Graaf and Allouch (2013) provide, based on a review of the literature, a comprehensive list of robot characteristics and user experience variables that are associated with the acceptance of social robots.

In terms of empirical evidence, the literature review of Naneva, Sarda Gou, Webb, and Prescott (2020) reports overall positive attitudes toward social robots. With a focus on education, Fridin and Belokopytov (2014) evaluated the acceptance of technology by teachers. Based on a sample of 18 teachers, they reported a positive association of the intention to use the Nao robot with attitudes and perceived usefulness; the overall perception of Nao was reportedly positive. However, other studies also report cautious attitudes of teachers toward social robots (Kennedy, Lemaignan, & Belpaeme, 2016; Reich-Stiebert & Eyssel, 2016). Based on a sample of 345 people, mainly university students, Reich-Stiebert and Eyssel (2015) reported a slight reluctance to engage in joint learning activities with social robots. Smakman, Konijn, Vogt, and Pankowska (2021) investigated the attitudes of important stakeholders (parents, teachers, school management, governmental policy makers, the robot industry, students) toward social robots in primary education ($N = 515$). By means of a cluster analysis, they identified five profiles: enthusiastic, practical, troubled, sceptic, and mindfully positive. As this study showed, there seems to be substantial variance in the attitudes toward social robots in education. This may be in line with the Eurobarometer 382 survey (2012), based on interviews with 26,751 citizens from the European Union. Of these, 34% named education as an area where the use of robots should be banned. Such attitudes by the public might be regarded as the social norm in the sense of the theory of planned behavior. Against this backdrop, it may be of particular importance to consider stakeholders and opinion leaders when integrating social robots into the classroom. A group of particular relevance might be parents (Smakman, Jansen, Leunen, & Konijn, 2020).

It is worth noting that technology acceptance studies usually rely on self-assessment instruments. Positive perceptions may be neither beneficial nor valid. For instance, students may perceive the robot as perfectly trustworthy and, therefore, do not rely on common sense (the comparative advantage of humans) when using the robot. Another example is perceived learning gains that do not necessarily equal actual learning outcomes (Nasir, Norman, Bruno, & Dillenbourg, 2020).

10.4 The Use of Lexi in Academic Writing

The Institute for Educational Management and Technologies at the University of St. Gallen investigated the acceptance of social robots as teaching assistants in higher education (Guggemos, Seufert, & Sonderegger, 2020). The importance of considering technology acceptance has been outlined in Sect. 3.3.2. Moreover, the empirical evidence on the use of social robots in higher education is scarce (Handke, 2018; Spolaôr & Benitti, 2017; Zhong & Xia, 2018). Existing studies primarily address their use in technical courses, for example, computer science (Abildgaard & Scharfe, 2012; Byrne, Rossi, & Doolan, 2017). From a conceptual point of view, social robots might be a valuable learning resource for students, especially in large-scale university courses (Byrne et al., 2017; Cooney & Leister, 2019). In such an environment, it is often difficult to adequately support students and answer individual questions. The use of human assistants for this purpose may not be feasible for various reasons, mainly budget constraints.

For the study, we used Lexi, a Pepper-model type (see Fig. 10.1). It can communicate verbally and nonverbally with users through speech, gestures, and facial expressions (Huang & Mutlu, 2014). In addition, Lexi can use a tablet placed on its chest to receive input and present output. Besides commercial use, for example, as a sales assistant in a shopping mall, Lexi is also used in educational settings, such as language learning among children (Tanaka et al., 2015). The setting for the present study was the introductory lecture of an academic writing course that is mandatory for all 1500 freshmen students at the University of St. Gallen. This setting is characterized by a pronounced heterogeneity in the prior knowledge of the students on the course material (Seufert & Spiroudis, 2017). Thus, this environment seems conceptually promising for the use of social robots as teaching assistants.

The unified theory of acceptance and use of technology (UTAUT) served as the theoretical framework for the study. According to this theory, the performance expectancy (PE), the effort expectancy (EE), and the social influence (SI) determine the intention of use (Venkatesh, Morris, Davis, & Davis, 2003). Sample items to capture these constructs are “Lexi could be useful for my learning success” (PE), “It would be easy for me to learn together with Lexi” (EE), and “My friends would appreciate it if I learned together with Lexi” (SI). Other constructs are only indirect predictors of the intention of use. Based on studies about the characteristics of social robots that potentially (indirectly) influence the intention of use (see Sect. 3.3.2), we selected four constructs, which are summarized in Table 10.2.

Social robots may be a specific kind of technology because they rely on AI to carry out tasks. In our case, a Microsoft Azure service was used to identify emotions based on a picture of a face. Study participants may have concerns about the handling of data collected during interactions with social robots (Lutz et al., 2019; Lutz & Tamó-Larrieux, 2020). Therefore, concerns about the use of the collected data have to be taken into account (anxiety backend). A sample item is “I would be worried about my privacy.” In order to separate these concerns from possible anxieties in general interaction with social robots (Graaf & Allouch, 2013), we also captured

Table 10.2 Characteristics of the robot, definitions, and sample items

Construct	Definition	Sample item
Trustworthiness (Heerink et al., 2010)	Degree to which students perceive the robot to be competent and act with integrity	I would trust in Lexi's advice
Adaptiveness (Heerink et al., 2010)	Degree to which students believe that the social robot adapts to their (learning) needs	Lexi could adapt to my personal learning needs
Social presence (Heerink et al., 2010)	Degree to which students perceive the robot to be a social entity	Lexi appeared to me like a real person
Appearance (Pandey & Gelin, 2018)	Perception of the acoustical and visual presence of the robot	Lexi has a nice appearance

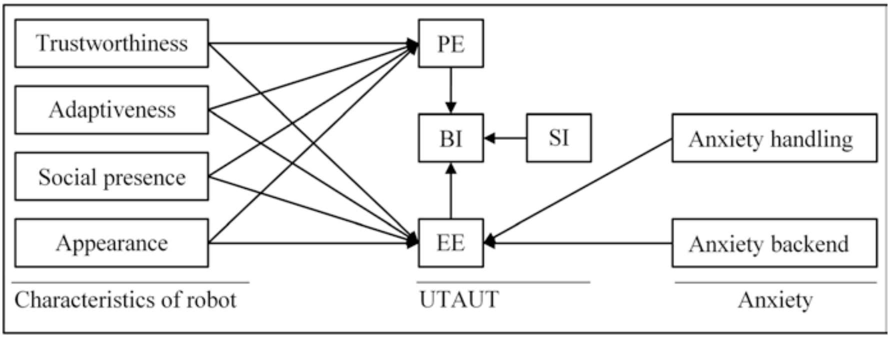

Fig. 10.3 Conceptual framework for predicting behavioral intention (BI) (Guggemos et al., 2020)

the construct "anxiety handling." A sample item is "I would be afraid of making mistakes." According to the UTAUT, anxieties negatively influence EE and thus have an (indirect) negative influence on the intention of use. Figure 10.3 summarizes the conceptual framework of the study.

In order to enable students to fairly assess the constructs presented in Table 10.2, Lexi had to provide students with a sample of its capabilities. It had to carry out activities that are representative in the context of learning at the current state of the art. For this purpose, the work of Cooney and Leister (2019) acted as the conceptual basis. Sample activities were developed to adequately represent the capabilities of the social robot (see Table 10.3). In addition to generic activities, such as greeting, typical problems and issues in academic writing were also addressed. For instance, Lexi explained how the plagiarism software worked: it guided students through the application and explained what output the algorithm of the plagiarism software generates and how the lecturer could then make a decision for each individual case. For the technical implementation, we collaborated with raumCode from Zurich, a company that specializes in social robots and AI. Lexi assisted for about 45 min during the lecture. It was connected to the projector in the venue and equipped with a headset. A video illustrates the activities according to Cooney and Leister (2019): https://unisg.link/lexi2020. After the lecture, a representative of raumCode explained

Table 10.3 Activities performed by Lexi during the course "Introduction to Academic Writing"

Activities	Tasks performed during the "Introduction to Academic Writing" course
Greeting	Introduces itself and the institute
Reading	Presents its aim: Assisting lecturers and students to foster learning Explains how plagiarism is detected by means of plagiarism software; outlines the software analyses, the outcome of the analytic process, and the decision-making process: The human is the final decider in every case (e.g., for a human-machine interaction and procedure based on complementary skills)
Alerting	Reminds the lecturer about presenting the functioning of the plagiarism software
Remote operations	Supports the lecturer by looking for sources on "greenwashing" in the database of the university's library Converses with a volunteer student: Accesses remote services during the conversation to determine the student's face characteristics, age, and mood ("happy," "surprised," "angry," "sad," and "neutral")
Clarification	Presents further material using the projector of the venue and demonstrates the functioning of the plagiarism software by giving an illustrative example
Motions	Follows the lecturer with its head; uses gestures to support its points and to express emotions

Note: Activities taken from Cooney and Leister (2019)

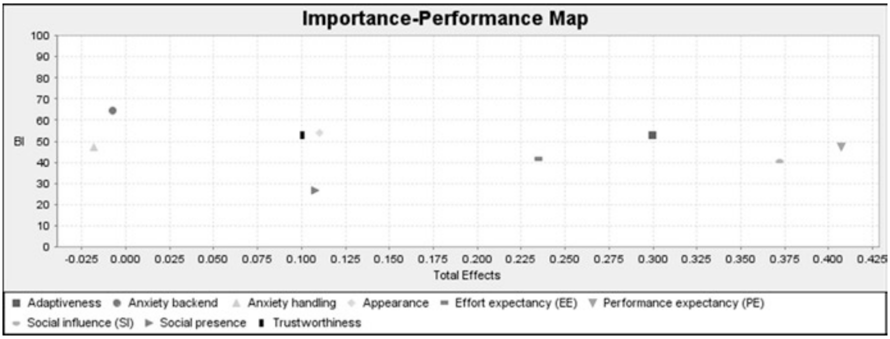

Fig. 10.4 Importance-performance map analysis (IPMA) for behavioral intention (BI) (Guggemos et al., 2020)

the functionality of the robot to the students. This may enable students to evaluate what is going on behind the scenes and, thus, understand the handling of their data.

After the lecture, students were asked to fill in a questionnaire that captured the constructs shown in Fig. 10.3 on a seven-point scale of rating, ranging from complete disagreement to complete agreement. The sample comprised 462 students, 65% of whom were male. The intended study programs were Business Administration (49%), Economics (22%), International Affairs (15%), Law (6%), and Law and Economics (8%). The average age of these first-semester students was 19.78 years (SD = 1.42 years).

The results of this study can be presented using an importance-performance map (Ringle & Sarstedt, 2016; Fig. 10.4).

The *x*-axis shows the strength of the association with the use intention (BI). For example, a value of 0.3 for adaptivity means that a perceived increase in the adaptivity of Lexi by one point on the seven-point rating scale yields an expected increase in the intention to use by 0.3 points. The *y*-axis of the importance-performance map shows the strength of the constructs on a percentage scale. For example, a value of 53 for adaptivity means that the perceived adaptivity is 53% of the theoretical maximum. The maximum would be achieved if students rate all adaptivity items at the highest possible value on the seven-point scale. Currently, the students in the sample rate the adaptivity of Lexi as medium. An importance-performance map enables users to identify constructs that are potentially promising for increasing BI. These would be constructs with a comparatively strong influence on BI, but at the same time a low performance or at least a performance that is well below 100%. In our study, all characteristics of the robot have a statistically significant positive influence on BI. However, the anxiety-related constructs (anxiety handling, anxiety backend) are not statistically significant and, in light of the statistical power of our study, do not have a practically relevant influence on BI.

Overall, the study showed that students tend not to have the intention to use Lexi as a learning aid—the performance of BI equals only 37% of the theoretical maximum. Following the idea of the importance-performance map, it would be promising to focus on the performance expectation, in other words, the perception of Lexi as a valuable learning aid. The current mediocre assessment is not surprising when research on high-quality learning arrangements (from the learner's perspective) is taken into account (Praetorius, Pauli, Reusser, Rakoczy, & Klieme, 2014). Lexi answered questions on a factual level which were not tailored to students' individual needs. Activities aimed at establishing a personal relationship between the lecturer and Lexi, such as using her name, were limited. Lexi also did not perform cognitive activation activities such as asking activating questions. Against this background, the students' assessment seems to be a realistic one. Substantially increasing PE seems to be difficult at the current technological state of the art. In addition, for personalized instruction it would be necessary to access student data, for example, from the learning management system, in order to retrieve student performance levels and then use this information in the interaction. If such a procedure is at all desirable, in light of privacy concerns, should be discussed.

SI could also be a factor in increasing the use intention of the robot. To this end, a communication strategy targeting the general public could be of value. For our part, we created a video introducing Lexi and its capabilities and distributed it via our social media channels and the website. The local press reported in a favorable way on the use of Lexi as a teaching assistant. Overall, it seems important to keep social influence in mind because it has a relatively strong impact on BI.

When looking at the characteristics of Lexi, adaptiveness stands out as the construct with the strongest influence on BI. As with human teachers, adaptivity seems to play an important role (Brühwiler & Blatchford, 2011). From the students' point of view, there is a clear need for improvement in adaptivity. This perception may also be realistic. However, it seems to be difficult to increase adaptiveness at the current technological state of the art, i.e., to consider students' prior knowledge, to provide learning material at an appropriate level of difficulty, to choose an appropriate learning pace, and to provide individualized feedback. To tackle this issue, it may be necessary to ensure that educational psychology and research on social robots and AI go hand in hand. One example could be the use of pupil dilation to measure cognitive load (van der Wel & van Steenbergen, 2018). Based on facial recognition (AI), the pupil diameter of students could be collected and the difficulty of the learning material adjusted accordingly to ensure appropriate cognitive load. Overall, it seems important to build on a strong conceptual basis for learning (Sweller, 2020). Afterward, it can be pointed out how AI can provide solutions that can be executed by social robots. However, it should be noted that well-trained human assistants would also probably not be able to achieve perfect adaptiveness.

Compared to adaptiveness, Lexi's other characteristics have a substantially lower influence on BI. Another remarkable finding is the low level of social presence (27%). The students do not have the impression that they are interacting with a real person. The findings regarding privacy concerns are also surprising. On the one hand, the students express strong concerns about privacy when interacting with the robot. On the other hand, these perceptions do not have an influence on their intention to use the robot. However, this may be explained by the "privacy paradox" (Acquisti, Brandimarte, & Loewenstein, 2015): people report serious concerns about privacy, yet voluntarily disclose private information and continue to use services, for example, social media, which they reportedly distrust. Lutz and Tamó-Larrieux (2020) found similar results for social robots.

In sum, at first glance the findings seem disappointing. Currently, there is considerable potential for increasing intention to use robots for learning purposes among university students of the social sciences. However, it was also possible to identify drivers that may be useful in increasing such user intention. Adaptiveness, in particular, seems to play an important role in the acceptance of social robots. As a limitation, it should be noted that the present study is based on correlative relationships. It cannot be ascertained whether causal effects are actually underlying these associations. Furthermore, it would be useful if students could work more intensively with robots in order to gain a better picture of the possibilities of social robots as learning aids.

10.5 Conclusions and Future Work

This chapter aims to provide an overview of the phenomenon of social robots in education. Evidence is available showing the value of physical presence. This is important because the higher cost involved in comparison to virtual agents has to be justified. The most commonly used type of robot in education is humanoid; a quasi-standard type is Nao from SoftBank Robotics. Social robots can interact with students using natural speech, motion, lights, and sounds. These characteristics contribute to the perceived personality of the robot. A further important social capability is empathy. Social robots can be described by their level of autonomy and intelligence. Autonomy is a continuum ranging from teleoperated to fully autonomous. A fully autonomous robot carries out sensing, planning, and acting without any intervention by the user. Since the desired level of autonomy is often hard to achieve at the current technological state of the art, researchers regularly apply the Wizard of Oz technique where the robot is teleoperated without the knowledge of the user. Due to the high complexity of educational settings, social robots have to be intelligent in order to achieve at least a moderate level of autonomy. Learning capabilities are regarded as a prerequisite for achieving intelligence.

In the classroom, various tasks have to be carried out which are codified in teaching standards. When identifying (sub-)tasks that can be undertaken by a robot, the criticality and complexity of the task need to be considered. Following the concept of hybrid intelligence, both the teacher and social robot may carry out the teaching tasks in collaboration and achieve a superior performance by utilizing the complementary strength of both parties.

The use of social robots has to meet ethical standards, namely, concerns about privacy, control, and responsibility. Moreover, AI-related issues such as the black-box problem and biased learning data have to be addressed. Besides ethical concerns, technology acceptance has to be considered; teachers, students, and parents, as important stakeholders, may be put into focus. Predictors for the intention to utilize social robots as learning assistants have been examined by presenting the case of academic writing; the perceived characteristic of the robot that best predicts the intention of use is the robot's adaptiveness.

Following the concept of hybrid intelligence, future research may not focus on robots in isolation but on how a teacher, in collaboration with the social robot, can best perform a specific task. The successful teacher may be the one who is competent in combining their own strength with that of the robot. When considering technology-related competencies, Seufert, Guggemos, and Sailer (2021), as well as Burkhard, Seufert, and Guggemos (2021), argue for the importance of such collaboration skills in an age of smart machines. For learning professionals in general, see Meier, Seufert, Guggemos, and Spirgi (2020). Future research could focus on the necessary knowledge, skills, and attitudes of pre- and in-service teachers (Seufert et al., 2021).

A promising avenue for further research could also be to explore how social robots can be integrated into a classroom ecosystem (Belpaeme & Tanaka, 2021; Seufert, Guggemos, & Moser, 2019). This would allow the generation of large-scale learning data that could be used to (further) train the robots. Moreover, ethical questions, for example, about privacy, can be addressed at the institutional level.

Finally, with social robots emerging as a new agent in the classroom, it might be promising to investigate how the orchestration of classroom activities could be effectively organized (Shahmoradi et al., 2019).

References

Abildgaard, J. R., & Scharfe, H. (2012). A geminoid as lecturer. In S. S. Ge, O. Khatib, J. J. Cabibihan, R. Simmons, & M. A. Williams (Eds.), *Social robotics—4th International Conference, ICSR 2012, Proceedings, Chengdu, China* (pp. 408–417). https://doi.org/10.1007/978-3-642-34103-8_41.

Acquisti, A., Brandimarte, L., & Loewenstein, G. (2015). Privacy and human behavior in the age of information. *Science, 347*(6221), 509–514. https://doi.org/10.1126/science.aaa1465

Admoni, H., & Scassellati, B. (2017). Social eye gaze in human-robot interaction: A review. *Journal of Human–Robot Interaction, 6*(1), 25. https://doi.org/10.5898/JHRI.6.1.Admoni

Ahmad, M. I., Mubin, O., & Orlando, J. (2017). Adaptive social robot for sustaining social engagement during long-term children–robot interaction. *International Journal of Human–Computer Interaction, 33*(12), 943–962. https://doi.org/10.1080/10447318.2017.1300750

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Alemi, M., Meghdari, A., & Ghazisaedy, M. (2015). The impact of social robotics on L2 learners' anxiety and attitude in English vocabulary acquisition. *International Journal of Social Robotics, 7*(4), 523–535. https://doi.org/10.1007/s12369-015-0286-y

Baraka, K., Alves-Oliveira, P., & Ribeiro, T. (2020). An extended framework for characterizing social robots. In C. Jost, B. Le Pévédic, T. Belpaeme, C. Bethel, D. Chrysostomou, N. Crook, et al. (Eds.), *Human-robot interaction* (pp. 21–64). Springer. https://doi.org/10.1007/978-3-030-42307-0_2

Bartneck, C., & Forlizzi, J. (2004). A design-centred framework for social human-robot interaction. In *Proceedings/RO-MAN 2004, 13th IEEE International Workshop on Robot and Human Interactive Communication: September 20–22, 2004, Kurashiki, Okayama, Japan* (pp. 591–594). IEEE Operations Center. https://doi.org/10.1109/ROMAN.2004.1374827.

Baxter, P., Ashurst, E., Read, R., Kennedy, J., & Belpaeme, T. (2017). Robot education peers in a situated primary school study: Personalisation promotes child learning. *PLoS One, 12*(5), e0178126. https://doi.org/10.1371/journal.pone.0178126

Beer, J. M., Fisk, A. D., & Rogers, W. A. (2014). Toward a framework for levels of robot autonomy in human-robot interaction. *Journal of Human–Robot Interaction, 3*(2), 74–99. https://doi.org/10.5898/JHRI.3.2.Beer

Belpaeme, T., Kennedy, J., Ramachandran, A., Scassellati, B., & Tanaka, F. (2018). Social robots for education: A review. *Science Robotics, 3*(21), 1–9. https://doi.org/10.1126/scirobotics.aat5954

Belpaeme, T., & Tanaka, F. (2021). Social robots as educators. In OECD (Ed.), *Digital education outlook 2021* (pp. 143–157). OECD. https://doi.org/10.1787/7fbfff45-en

Bransford, J., Brown, A. L., & Cocking, R. R. (2000). *How people learn: Brain, mind, experience, and school* (Expanded edition). National Academy Press.

Brščić, D., Kidokoro, H., Suehiro, Y., & Kanda, T. (2015). Escaping from children's abuse of social robots. In J. A. Adams, W. Smart, B. Mutlu, & L. Takayama (Eds.), *Proceedings of the 2015 ACM/IEEE International Conference on Human-Robot Interaction* (pp. 59–66). ACM. https://doi.org/10.1145/2696454.2696468

Brühwiler, C., & Blatchford, P. (2011). Effects of class size and adaptive teaching competency on classroom processes and academic outcome. *Learning and Instruction, 21*(1), 95–108. https://doi.org/10.1016/j.learninstruc.2009.11.004

Burkhard, M., Seufert, S., & Guggemos, J. (2021a). Paradigm shift in human-machine interaction: A new learning framework for required competencies in the age of artificial intelligence? In *13th International Conference on Computer Supported Education*. https://doi.org/10.5220/0010370300730083.

Burkhard, M., Seufert, S., & Guggemos, J. (2021b). Relative strengths of teachers and smart machines: Towards an augmented task sharing. In *13th International Conference on Computer Supported Education*. https://doi.org/10.5220/0010370300730083.

Byrne, B. M., Rossi, A., & Doolan, M. (2017). Humanoid robots attending lectures. In *Proceedings of the 9th International Conference on Education Technology and Computers, ICETC, Barcelona, Spain*. https://doi.org/10.1145/3175536.3175556

CCSSO. (2021). *InTASC model core teaching standards and learning progressions for teachers 1.0*. Council of Chief State School Officers (CCSSO). Retrieved from https://ccsso.org/resource-library/intasc-model-core-teaching-standards

Cheng, Y.-W., Sun, P.-C., & Chen, N.-S. (2018). The essential applications of educational robot: Requirement analysis from the perspectives of experts, researchers and instructors. *Computers & Education, 126*, 399–416. https://doi.org/10.1016/j.compedu.2018.07.020

Ching, Y.-H., Hsu, Y.-C., & Baldwin, S. (2018). Developing computational thinking with educational technologies for young learners. *TechTrends, 62*(6), 563–573. https://doi.org/10.1007/s11528-018-0292-7

Conti, D., Cirasa, C., Di Nuovo, S., & Di Nuovo, A. (2020). Robot, tell me a tale! *Interaction Studies, 21*(2), 220–242. https://doi.org/10.1075/is.18024.con

Cooney, M., & Leister, W. (2019). Using the Engagement Profile to design an engaging robotic teaching assistant for students. *Robotics, 8*(1), 1–26. https://doi.org/10.3390/robotics8010021

Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid Intelligence. *Business & Information Systems Engineering, 61*(5), 637–643. https://doi.org/10.1007/s12599-019-00595-2

Eurobarometer 382. (2012). *Public attitudes towards robots*. European Commission.

Feuerriegel, S., Dolata, M., & Schwabe, G. (2020). Fair AI. *Business & Information Systems Engineering, 62*(4), 379–384. https://doi.org/10.1007/s12599-020-00650-3

Fong, T., Nourbakhsh, I., & Dautenhahn, K. (2003). A survey of socially interactive robots. *Robotics and Autonomous Systems, 42*(3–4), 143–166. https://doi.org/10.1016/S0921-8890(02)00372-X

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Fridin, M., & Belokopytov, M. (2014). Acceptance of socially assistive humanoid robot by preschool and elementary school teachers. *Computers in Human Behavior, 33*, 23–31. https://doi.org/10.1016/j.chb.2013.12.016

Goel, A. K., & Polepeddi, L. (2016). *Jill Watson: A virtual teaching assistant for online education.* Retrieved from http://hdl.handle.net/1853/59104.

Graaf, M. M. A. d., & Allouch, S. B. (2013). Exploring influencing variables for the acceptance of social robots. *Robotics and Autonomous Systems, 61*(12), 1476–1486. https://doi.org/10.1016/j.robot.2013.07.007

Guggemos, J. (2021). On the predictors of computational thinking and its growth at the high-school level. *Computers & Education, 161*, 104060. https://doi.org/10.1016/j.compedu.2020.104060

Guggemos, J., & Seufert, S. (2021). Teaching with and teaching about technology—Evidence for professional development of in-service teachers. *Computers in Human Behavior, 115*, 106613. https://doi.org/10.1016/j.chb.2020.106613

Guggemos, J., Seufert, S., & Sonderegger, S. (2020). Humanoid robots in higher education: Evaluating the acceptance of Pepper in the context of an academic writing course using the UTAUT. *British Journal of Educational Technology, 51*(5), 1864–1883. https://doi.org/10.1111/bjet.13006

Gunning, D., Stefik, M., Choi, J., Miller, T., Stumpf, S., & Yang, G.-Z. (2019). XAI-Explainable artificial intelligence. *Science Robotics, 4*(37), eaay7120. https://doi.org/10.1126/scirobotics.aay7120

Handke, J. (2018). Digitale Hochschullehre – Vom einfachen Integrationsmodell zur Künstlichen Intelligenz. In U. Dittler & C. Kreidl (Eds.), *Hochschule der Zukunft* (pp. 249–263). Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-20403-7_15

Handke, J. (2020). *Humanoide Roboter: Showcase, partner und Werkzeug* (1st ed.). Tectum Wissenschaftsverlag.

Heerink, M., Kröse, B., Evers, V., & Wielinga, B. (2010). Assessing acceptance of assistive social agent technology by older adults: The Almere Model. *International Journal of Social Robotics, 2*(4), 361–375. https://doi.org/10.1007/s12369-010-0068-5

Henschel, A., Laban, G., & Cross, E. S. (2021). What makes a robot social? A review of social robots from science fiction to a home or hospital near you. *Current Robotics Reports, 2*(1), 9–19. https://doi.org/10.1007/s43154-020-00035-0

Hood, D., Lemaignan, S., & Dillenbourg, P. (2015). When children teach a robot to write. In J. A. Adams, W. Smart, B. Mutlu, & L. Takayama (Eds.), *Proceedings of the 2015 ACM/IEEE International Conference on Human–Robot Interaction* (pp. 83–90). ACM. https://doi.org/10.1145/2696454.2696479.

Huang, C.-M., & Mutlu, B. (2014). Learning-based modeling of multimodal behaviors for human-like robots. In G. Sagerer, M. Imai, T. Belpaeme, & A. Thomaz (Eds.), *HRI'14: Proceedings of the 2014 ACM/IEEE International Conference on Human-Robot Interaction* (pp. 57–64). ACM Press. https://doi.org/10.1145/2559636.2559668

Ifenthaler, D. (2015). Learning analytics. In J. M. Spector (Ed.), *The SAGE encyclopedia of educational technology* (pp. 447–451). SAGE. https://doi.org/10.4135/9781483346397.n187

Jamet, F., Masson, O., Jacquet, B., Stilgenbauer, J.-L., & Baratgin, J. (2018). Learning by teaching with humanoid robot: A new powerful experimental tool to improve children's learning ability. *Journal of Robotics, 2018*, 1–11. https://doi.org/10.1155/2018/4578762

Kärner, T., Warwas, J., Krannich, M., & Weichsler, N. (2021). How does information consistency influence prospective teachers' decisions about task difficulty assignments? A within-subject experiment to explain data-based decision-making in heterogeneous classes. *Learning and Instruction, 74*, 101440. https://doi.org/10.1016/j.learninstruc.2020.101440

Kennedy, J., Lemaignan, S., & Belpaeme, T. (2016). The cautious attitude of teachers towards social robots in schools. In *Robots 4 Learning Workshop at IEEE RO-MAN*.

Khanal, S. R., Barroso, J., Lopes, N., Sampaio, J., & Filipe, V. (2018). Performance analysis of Microsoft's and Google's Emotion Recognition API using pose-invariant faces. In *Proceedings of the 8th International Conference on Software Development and Technologies for Enhancing Accessibility and Fighting Info-exclusion* (pp. 172–178). ACM. https://doi.org/10.1145/3218585.3224223.

Leite, I., Castellano, G., Pereira, A., Martinho, C., & Paiva, A. (2014). Empathic robots for long-term interaction. *International Journal of Social Robotics, 6*(3), 329–341. https://doi.org/10.1007/s12369-014-0227-1

Li, J. (2015). The benefit of being physically present: A survey of experimental works comparing copresent robots, telepresent robots and virtual agents. *International Journal of Human-Computer Studies, 77*, 23–37. https://doi.org/10.1016/j.ijhcs.2015.01.001

Lutz, C., Schöttler, M., & Hoffmann, C. P. (2019). The privacy implications of social robots: Scoping review and expert interviews. *Mobile Media and Communication, 7*(3), 412–434. https://doi.org/10.1177/2050157919843961

Lutz, C., & Tamó-Larrieux, A. (2020). The robot privacy paradox: Understanding how privacy concerns shape intentions to use social robots. *Human–Machine Communication, 1*, 87–111. https://doi.org/10.30658/hmc.1.6

Mavridis, N. (2015). A review of verbal and non-verbal human–robot interactive communication. *Robotics and Autonomous Systems, 63*, 22–35. https://doi.org/10.1016/j.robot.2014.09.031

Meier, C., Seufert, S., Guggemos, J., & Spirgi, J. (2020). Learning organizations in the age of smart machines. In D. Ifenthaler, S. Hofhues, M. Egloffstein, & C. Helbig (Eds.), *Digital transformation of learning organizations* (pp. 77–94). Springer. https://doi.org/10.1007/978-3-030-55878-9_5

Mori, M., MacDorman, K., & Kageki, N. (2012). The Uncanny Valley. *IEEE Robotics and Automation Magazine, 19*(2), 98–100. https://doi.org/10.1109/MRA.2012.2192811

Mosavi, A., & Varkonyi-Koczy, A. R. (2016). Integration of machine learning and optimization for robot learning. In R. Jabłoński & R. Szewczyk (Eds.), *Advances in Intelligent Systems and Computing. Recent Global Research and Education: Proceedings of the 15th International*

Conference on Global Research and Education (pp. 349–355). Springer. https://doi.org/10.1007/978-3-319-46490-9_47.

Mou, Y., Shi, C., Shen, T., & Xu, K. (2020). A systematic review of the personality of robot: Mapping its conceptualization, operationalization, contextualization and effects. *International Journal of Human–Computer Interaction, 36*(6), 591–605. https://doi.org/10.1080/10447318.2019.1663008

Mousavinasab, E., Zarifsanaiey, N., Niakan, R., Kalhori, S., Rakhshan, M., Keikha, L., & Ghazi Saeedi, M. (2021). Intelligent tutoring systems: A systematic review of characteristics, applications, and evaluation methods. *Interactive Learning Environments, 29*(1), 142–163. https://doi.org/10.1080/10494820.2018.1558257

Mubin, O., Stevens, C. J., Shahid, S., Mahmud, A. A., & Dong, J.-J. (2013). A review of the applicability of robots in education. *Technology for Education and Learning, 1*(1), 1–7. https://doi.org/10.2316/Journal.209.2013.1.209-0015

Naneva, S., Sarda Gou, M., Webb, T. L., & Prescott, T. J. (2020). A systematic review of attitudes, anxiety, acceptance, and trust towards social robots. *International Journal of Social Robotics, 12*(6), 1179–1201. https://doi.org/10.1007/s12369-020-00659-4

Nasir, J., Norman, U., Bruno, B., & Dillenbourg, P. (2020). When positive perception of the robot has no effect on learning. In F. Ferland & D. Morocco (Eds.), *Robots with heart, mind, and soul: The 29th IEEE International Conference on Robot and Human Interactive Communication: 31 August-04 September 2020* (pp. 313–320). IEEE. https://doi.org/10.1109/RO-MAN47096.2020.9223343

Niculescu, A., van Dijk, B., Nijholt, A., Li, H., & See, S. L. (2013). Making social robots more attractive: The effects of voice pitch, humor and empathy. *International Journal of Social Robotics, 5*(2), 171–191. https://doi.org/10.1007/s12369-012-0171-x

Nishio, S., Ishiguro, H., & Hagit, N. (2007). Geminoid: Teleoperated android of an existing person. In A. C. de Pina Filho (Ed.), *Humanoid robots: New developments*. I-Tech Education and Publishing. https://doi.org/10.5772/4876

Pandey, A. K., & Gelin, R. (2018). A mass-produced sociable humanoid robot: Pepper: The first machine of its kind. *IEEE Robotics and Automation Magazine, 25*(3), 40–48. https://doi.org/10.1109/MRA.2018.2833157

Papadopoulos, I., Lazzarino, R., Miah, S., Weaver, T., Thomas, B., & Koulouglioti, C. (2020). A systematic review of socially assistive robots in pre-tertiary education. *Computers and Education, 155*, 103924. https://doi.org/10.1016/j.compedu.2020.103924

Pardo, A., & Siemens, G. (2014). Ethical and privacy principles for learning analytics. *British Journal of Educational Technology, 45*(3), 438–450. https://doi.org/10.1111/bjet.12152

Praetorius, A.-K., Klieme, E., Herbert, B., & Pinger, P. (2018). Generic dimensions of teaching quality: The German framework of three basic dimensions. *ZDM, 50*(3), 407–426. https://doi.org/10.1007/s11858-018-0918-4

Praetorius, A.-K., Pauli, C., Reusser, K., Rakoczy, K., & Klieme, E. (2014). One lesson is all you need? Stability of instructional quality across lessons. *Learning and Instruction, 31*, 2–12. https://doi.org/10.1016/j.learninstruc.2013.12.002

Reich-Stiebert, N., & Eyssel, F. (2015). Learning with educational companion robots? Toward attitudes on education robots, predictors of attitudes, and application potentials for education robots. *International Journal of Social Robotics, 7*(5), 875–888. https://doi.org/10.1007/s12369-015-0308-9

Reich-Stiebert, N., & Eyssel, F. (2016). Robots in the classroom: What teachers think about teaching and learning with education robots. In A. Agah, J.-J. Cabibihan, A. M. Howard, M. A. Salichs, & H. He (Eds.), *Social robotics* (pp. 671–680). Springer International Publishing.

Riek, L. (2012). Wizard of Oz studies in HRI: A systematic review and new reporting guidelines. *Journal of Human-Robot Interaction, 1*(1), 119–136. https://doi.org/10.5898/JHRI.1.1.Riek

Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. *Industrial Management and Data Systems, 116*(9), 1865–1886. https://doi.org/10.1108/IMDS-10-2015-0449

Salem, M., Kopp, S., Wachsmuth, I., Rohlfing, K., & Joublin, F. (2012). Generation and evaluation of communicative robot gesture. *International Journal of Social Robotics, 4*(2), 201–217. https://doi.org/10.1007/s12369-011-0124-9

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers and Education, 128*, 13–35. https://doi.org/10.1016/j.compedu.2018.09.009

Seeber, I., Bittner, E., Briggs, R. O., Vreede, T. d., Vreede, G.-J. d., Elkins, A., Maiera, R., Merza, A. B., Oeste-Reiße, S., Randrupf, N., Schwabeg, G., & Söllnereh, M. (2020). Machines as teammates: A research agenda on AI in team collaboration. *Information and Management, 57*(2), 103174. https://doi.org/10.1016/j.im.2019.103174

Serholt, S., Barendregt, W., Vasalou, A., Alves-Oliveira, P., Jones, A., Petisca, S., & Paiva, A. (2017). The case of classroom robots: Teachers' deliberations on the ethical tensions. *AI and Society, 32*(4), 613–631. https://doi.org/10.1007/s00146-016-0667-2

Seufert, Guggemos, & Moser. (2019). Digitale Transformation in Hochschulen: auf dem Weg zu offenen Ökosystemen. *Zeitschrift Für Hochschulentwicklung, 14*(2), 85–107. https://doi.org/10.3217/zfhe-14-02/05

Seufert, S., Guggemos, J., & Sailer, M. (2021). Technology-related knowledge, skills, and attitudes of pre- and in-service teachers: The current situation and emerging trends. *Computers in Human Behavior, 115*, 106552. https://doi.org/10.1016/j.chb.2020.106552

Seufert, S., & Spiroudis, E. (2017). Wissenschaftliche Schreibkompetenz in der Studieneingangsphase fördern: Erfahrungen mit einem Rückmelde und Bewertungsraster (Rubric). *Zeitschrift Schreiben, 15*, 1–9.

Shahmoradi, S., Olsen, J. K., Haklev, S., Johal, W., Norman, U., Nasir, J., & Dillenbourg, P. (2019). Orchestration of robotic activities in classrooms: Challenges and opportunities. In M. Scheffel, J. Broisin, V. Pammer-Schindler, A. Ioannou, & J. Schneider (Eds.), *Lecture notes in computer science. Transforming learning with meaningful technologies* (Vol. 11722, pp. 640–644). Springer International Publishing. https://doi.org/10.1007/978-3-030-29736-7_57

Sharkey, A. J. C. (2016). Should we welcome robot teachers? *Ethics and Information Technology, 18*(4), 283–297. https://doi.org/10.1007/s10676-016-9387-z

Smakman, M. H. J., Jansen, B., Leunen, J., & Konijn, E. A. (2020). Acceptable social robots in education: A value sensitive parent perspective. In *Proceedings of INTED2020 Conference* (pp. 7946–7953).

Smakman, M. H. J., Konijn, E. A., Vogt, P., & Pankowska, P. (2021). Attitudes towards social robots in education: Enthusiast, practical, troubled, sceptic, and mindfully positive. *Robotics, 10*(1), 24. https://doi.org/10.3390/robotics10010024

Sohn, K., & Kwon, O. (2020). Technology acceptance theories and factors influencing artificial intelligence-based intelligent products. *Telematics and Informatics, 47*, 101324. https://doi.org/10.1016/j.tele.2019.101324

Spolaôr, N., & Benitti, F. B. (2017). Robotics applications grounded in learning theories on tertiary education: A systematic review. *Computers and Education, 112*, 97–107. https://doi.org/10.1016/j.compedu.2017.05.001

Suchman, M. C. (1995). Managing legitimacy: Strategic and institutional approaches. *Academy of Management Review, 20*(3), 571–610. https://doi.org/10.5465/amr.1995.9508080331

Sweller, J. (2020). Cognitive load theory and educational technology. *Educational Technology Research and Development, 68*(1), 1–16. https://doi.org/10.1007/s11423-019-09701-3

Tanaka, F., Isshiki, K., Takahashi, F., Uekusa, M., Sei, R., & Hayashi, K. (2015). Pepper learns together with children: Development of an educational application. In T. Asfour (Ed.), *15th International Conference on Humanoid Robots (Humanoids), IEEE-RAS: November 3–5, 2015, Seoul, Korea* (pp. 270–275). IEEE. https://doi.org/10.1109/HUMANOIDS.2015.7363546

Vallor, S., & Bekey, G. A. (2017). Artificial intelligence and the ethics of self-learning robots. In P. Lin, R. Jenkins, & K. Abney (Eds.), *Robot Ethics 2.0: From autonomous cars to artificial intelligence* (pp. 338–353). Oxford University Press.

Van den Berghe, R., Verhagen, J., Oudgenoeg-Paz, O., van der Ven, S., & Leseman, P. (2019). Social robots for language learning: A review. *Review of Educational Research, 89*(2), 259–295. https://doi.org/10.3102/0034654318821286

Van der Wel, P., & van Steenbergen, H. (2018). Pupil dilation as an index of effort in cognitive control tasks: A review. *Psychonomic Bulletin & Review, 25*(6), 2005–2015. https://doi.org/10.3758/s13423-018-1432-y

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Vogt, P., van den Berghe, R., Haas, M. de, Hoffman, L., Kanero, J., Mamus, E., Montanier, J.-M., Oranc, C., Oudgenoeg-Paz, O., Garcia, D. H., Papadopoulos, F., Schodde, T., Verhagen, J., Wallbridge, C. D., Willemsen, B., de Wit, J., Belpaeme, T., Göksun, T., Kopp, S., Krahmer, E., Küntay, A. C., Leseman, P., & Pandey, A. K. (2019). , Second language tutoring using social robots: A large-scale study. In *Proceedings of the 14th ACM/IEEE International Conference on Human-Robot Interaction* (pp. 497–505). IEEE Press. https://doi.org/10.1109/HRI.2019.8673077.

Wang, P. (2019). On defining artificial intelligence. *Journal of Artificial General Intelligence, 10*(2), 1–37. https://doi.org/10.2478/jagi-2019-0002

Woo, H., LeTendre, G. K., Pham-Shouse, T., & Xiong, Y. (2021). The use of social robots in classrooms: A review of field-based studies. *Educational Research Review, 33*, 100388. https://doi.org/10.1016/j.edurev.2021.100388

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1). https://doi.org/10.1186/s41239-019-0171-0

Zhong, B., & Xia, L. (2018). A systematic review on exploring the potential of educational robotics in mathematics education. *International Journal of Science and Mathematics Education, 12*(5), 491. https://doi.org/10.1007/s10763-018-09939-y