Acceptance and Applicability of Educational Robots

—

Evaluating Factors Contributing to a Successful Introduction

of Social Robots into Education

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SUMMARY

The use of robots in the area of education is rapidly gaining momentum. Education faces restructuring and modernization in the forthcoming age of robots, thus necessitating research meeting the requirements of this development. In this, focusing on robots' acceptance and applicability in educational contexts, right from the very beginning, is crucial. Therefore, this dissertation thesis has addressed this issue. It has striven to evaluate factors which contribute to a successful introduction of robots into education in a systematic manner. The strengths of the current work lie in its interdisciplinary nature, theoretical fundament, and the application of empirical and experimental methods.

In practical terms, a set of studies have offered insights on how the implementation and application of robots in education could be facilitated. To do so, they operated on three different levels: First, the focus was on end users' attitudes toward educational robots. It was shown that their attitudes and willingness to use educational robots were moderate. However, the results also indicated that the acceptance of educational robots could be fostered by the promotion of people's general technical interest and a targeted use of robots in individual or small-group learning activities, in domains related to science and technology. In addition, it was found that user involvement in an educational robot's design process can increase people's general acceptance of educational robots. Second, the work focused on how to effectively design a human-robot interaction (HRI) for learning purposes by building upon the cooperative learning paradigm found in educational literature. Actual HRI experiments confirmed that a robot's physical presence was beneficial for the learning experience, and implied that positive interdependence with a robot, social support from it, and mutual feedback about the learning process were positively related to the learning experience and the learners' perception of the robot. Third, when tackling the issue of the ideal educational robot design, it has become clear that people's perception of robots is influenced by context- and person-specific factors. To

trigger a higher acceptance of educational robots, robotics research should match potential end users' educational robot design concepts, for example, machinelike appearance and functionality as well as privacy and safety requirements.

Taken together, this dissertation presents a sound basis for identifying issues related to the implementation and application of educational robots. However, research is still far from having completed the development of strategies for implementing and using social robots in education meaningfully. Consequently, potential future research directions will be discussed in light of the obtained results.

1 INTRODUCTION

In November 1984, under the headline, "Revolution in the classroom: Computer becomes mandatory", the German magazine *Der Spiegel* reported on German education ministers' demands to introduce computers into schools and to force teachers to incorporate computers into their teaching ("Alarm in den Schulen", 1984). This development was contentious and divisive. In particular, some teachers rejected computers in schools and even feared that students could become isolated, losing touch with reality. Now, more than 30 years later, a representative survey in German schools has revealed that nearly 50 percent of teachers use computers for teaching at least once a week and more than 50 percent agree that the use of computers improves students' performance (Lorenz, Endberg, & Eickelmann, 2016).

Meanwhile, the evolution of technology in education is still continuing and currently students and teachers are being confronted with one of the latest developments, namely *educational robots*. Statistics from the International Federation of Robotics clearly indicate an upward trend in the of use of robots in the educational sector—and this increase is very likely to continue (International Federation of Robotics, 2017). William Gibson (1996) commented that, "the future is already here—it's just not evenly distributed". Confirming this view, individual efforts to use robots to support educational activities can be observed. However, the comprehensive distribution of robots throughout schools and higher education is still a future vision. In fact, the use of educational robots is the exception rather than the rule and has a science-fiction-like appeal for many European students and teachers.

Consequently, whether the educational landscape will undergo a far-reaching change in the future, making robots indispensable in classrooms and lectures, is questionable. If such a change were to happen, how would people respond? More importantly, would potential stakeholders, like students and teachers, accept robots as learning tools, and if so, how could robots provide effective assistance for learning and teaching? Moreover, which factors would

have to be considered before robots could be introduced into teaching and learning processes? Whether the current educational system is willing to incorporate educational robots, and what would be necessary to prevent them from being regarded as unusable and inappropriate tools, must be clarified. The present work aims to answer precisely these questions. More specifically, factors that will contribute to the future introduction of social robots into education have been investigated on three levels: Firstly, the acceptance of educational robots has been evaluated. Secondly, an opportunity to structure human-robot learning effectively was approached by building on cooperative learning principles. Thirdly, the ideal educational robot design has been considered from potential end users' perspective. Thus, this thesis contributes to the interdisciplinary discourse on robots in education and proposes practical implications for field applications of educational robots.

1.1 Toward a Definition of Educational Robots

Attempting a definition of 'educational robots' gives rise to various specifications of what constitutes robots in education. From a general perspective, educational robots can be classified as assistive robots, which are intended to support or aid users in different environments such as schools (Feil-Seifer & Matarić, 2005). In that sense, educational robots are used as learning tools, either to teach students about robots per se, or to teach technical skills through the manipulation of and interaction with robots (see Eguchi, 2012). In fact, the use of educational robots is predominantly limited to fields related to science, technology, engineering, and mathematics (STEM). The literature provides ample evidence that using robots for technology-oriented teaching methods has considerable potential (e.g., Benitti, 2012; Bravo, González, & González, 2017, Merdan, Lepuschitz, Koppensteiner, & Balogh, 2017; Mubin, Stevens, Shahid, Al Mahmud, & Dong, 2013). However, in recent years, more and more researchers are investigating the potential of using educational robots in non-technical subject areas, such as linguistics, biology, or social sciences and humanities. As a result, educational robots are used

in different ways and are attributed distinctive roles: When educational robots are used in STEM-related domains, they are considered as either (a) objects for learning and teaching programming or (b) a learning focus in itself. In a cross-curricular application placing greater emphasis on the educational use, robots are regarded as (c) learning collaborators (see Miller, Nourbakhsh, & Siegwart, 2008). Role (a) focuses on programming "in order to create a concrete physical manifestation of the art of computer programming", while role (b) comprises "the creation and use of a physical robot as a goal in and of itself" (Miller et al., 2008, p. 1284). Role (c) implies that they are used "as an all-season companion, aide, and even intellectual foil" (Miller et al., 2008, p. 1284). Considering the increasing use of educational robots as learning collaborators in more social subject areas emphasizes their socially interactive function. Therefore, educational robots as learning collaborators can be regarded as socially assistive robots that offer support and assistance through social interactions to assist humans in their learning (Feil-Seifer & Matarić, 2005). This context emphasizes the establishment of social interactions with humans based on human-like behavioral traits, communication, or emotions (Duffy, 2003).

Combining the different definitions and descriptions, the following working definition of educational robots will be used in this thesis: Educational robots in their role as learning partners are categorized as socially assistive robots for educational purposes. As they fulfil a didactic function, they can be considered to be learning companions which provide academic support and facilitate learning and teaching efforts through social interactions. Specifically, educational robots can be used as personal tutors to help students edit tasks or promote individual learning processes. As teachers' assistants, they can help to arrange lessons or measure students' learning progress. Educational robots can be used, for instance, in various disciplines and provide information on specific topics, test learning progress, correct errors, or provide feedback on students' results—just to mention some of their areas of application.

However, the development of this sort of advanced educational robot described here, is still in its infancy. Such an educational robot would need to operate highly autonomously, have excellent speech recognition and output, perceive its environment reliably, move safely and fluidly, respond flexibly to different users' diverse requirements and much more; and it should be able to do it all without requiring intervention from an operator. The features and functions presupposed here are severely limited by the current state of the art. Due to these limitations, research in the field of social human-robot interaction (HRI) must often rely on simulations of these functions and properties. The Wizard-of-Oz technique (Kelley, 1984) allows the robot to be controlled remotely and has therefore been adopted in the present research.

1.2 Acceptance of Educational Robots

Investigations on people's attitudes toward educational robots is becoming progressively important in HRI research, since results suggest that attitudes can determine the future acceptance of robots (e.g., Fridin & Belokopytov, 2014; Nomura, Kanda, & Suzuki, 2006; Serholt et al., 2014). In turn, educational robots' acceptance must be considered essential for their fruitful introduction into educational contexts.

The findings on people's attitudes toward educational robots are inconsistent, pointing in both positive and negative directions (e.g., Choi, Lee, & Han, 2008; European Commission, 2012; Fridin & Belokopytov, 2014; Serholt et al., 2014; Shin & Kim, 2007). To illustrate, their entertainment function (e.g., Liu, 2010), provision of information, or documentation of students' learning progress were identified as positive aspects of educational robots (e.g., Serholt & Barendregt, 2014; Serholt et al., 2014; Shin & Kim, 2007). In contrast, people feared that robots lacked emotional capabilities (e.g., Shin & Kim, 2007), could distract children from learning (e.g., Lin, Liu, Chang, & Yeh, 2009; Serholt et al., 2014), or might replace teachers and influence students negatively (e.g., Lee, Lee, Kye, & Ko, 2008; Serholt et al., 2014).

Since robots could prospectively also become part of German educational environments, investigating German students' and teachers' attitudes toward educational robots might be worthwhile. By evaluating future stakeholders' expectations and concerns with respect to learning and teaching with robots, potential obstacles could be addressed, thus increasing the future acceptance of educational robots. Students' and school teachers' suggestions for an optimal implementation of robots in different learning situations and subjects appear to be especially relevant and will therefore be a focus of the studies reported here (Reich-Stiebert & Eyssel, 2015, 2016). As will be further outlined in this thesis, German university students and school teachers express only a moderate acceptance of educational robots. Therefore, the present work will also aim to identify strategies for improving end users' attitudes and increasing educational robot acceptance (Reich-Stiebert & Eyssel, 2017).

1.3 Cooperative Learning with Educational Robots

Focusing on transdisciplinary knowledge to address open questions and evaluating problems from multiple angles, is beginning to become standard practice in HRI research (see Baxter, Kennedy, Senft, Lemaignan, & Belpaeme, 2016; Eyssel, 2016). Previous approaches to applying robots in education have demonstrated that this line of research is similarly influenced by an integrative tactic (e.g., by combining knowledge from areas such as linguistics, social sciences, or psychology). In an attempt to explore successful HRI models for educational purposes, recent works have increasingly adopted psychological and pedagogical perspectives (e.g., Catlin & Blamires, 2010; Damaševičius, Narbutaitė, Plauska, & Blažauskas, 2017; Jones et al., 2015; Saerbeck, Schut, Bartneck, & Janse, 2010). However, so far, these efforts are not very advanced and there is still little understanding of how to implement psychological and educational concepts into human-robot learning activities in a meaningful way.

Nevertheless, aligning with sound teaching and learning theories will lead "any educational innovation, including robotics, to success" (Alimisis, 2012, p. 7). Thus, research

on the successful implementation of educational robots will benefit greatly from the use of elaborated theoretical models from psychology and pedagogy. In turn, research is regarded as providing "evidence for or against the validity of [a] theory" (Burr et al., 1973, p. 290), which then can be translated into valuable information that can be used in the field of application. This thesis therefore aims to contribute to the growing area of educational HRI research by adopting theory-driven empirical approaches to study factors which influence the applicability of educational robots. To achieve this, the work refers to a popular and highly recognized pedagogical model of human-human interaction for successful learning—namely cooperative learning (see Johnson & Johnson, 1994, 2009).

Johnson and Johnson (1994, 2009) essentially established the concept of cooperative learning, describing it as a method in which students learn together to accomplish shared goals. Cooperative learning consists of various teaching methods in which students collaborate in small groups to promote each other's learning (Slavin, 1996). There is ample evidence to support the power of cooperative learning, based on frequently-used measures of learning success, such as achievement, enhanced self-esteem, social support between learners, or positive attitudes toward the subject (e.g., Jenkins, Antil, Wayne, & Vadasy, 2003; Johnson, Johnson, & Smith, 1998; Kyndt, Raes, Lismont, Timmers, Cascallar, & Dochy, 2013; Slavin, 1996). The literature on cooperative learning has its roots in the social interdependence theory (Johnson & Johnson, 2005, 2009), which was introduced to describe cooperation and competition in small groups (Deutsch, 1949). It is based on different assumptions on social interdependence (Deutsch, 1949), and Johnson and Johnson identified five essential components which contribute to its efficacy (Johnson & Johnson, 1989, 2009). These include social interdependence, individual accountability, direct face-to-face interaction, appropriate use of social skills, and group processing.

According to the basic idea of social interdependence, learners depend on each other to achieve common goals. As a result, each individual's effort benefits both the group members

and the individual itself (Johnson & Johnson, 1992, 2009). Individual accountability, which includes the commitment to completing one's share of the work and to contributing to the group's progress (Johnson & Johnson, 2005, 2009), is strongly related to positive interdependence. Direct face-to-face interaction comprises the aspect of physical proximity which augments effective communication. Direct interaction, for example, supports problem-solving, assistance between group members, the exchange of resources, or provision of feedback (Johnson & Johnson, 2009). Efficient cooperation further depends on the appropriate use of social skills. This includes, for example, unambiguous communication, social supportive behaviors, or constructive conflict management (Johnson & Johnson, 2005, 2009). Finally, group processing complements successful cooperative learning by reflecting the learning process and providing feedback on helpful and unhelpful activities (Johnson & Johnson, 2005, 2009).

These elements were evaluated prominently in the current work: The first aim was to test the practicability of implementing positive interdependence, direct face-to-face interaction, social support, and group processing in dyadic human-robot learning. Owing to the strong interrelation of positive interdependence and individual accountability (Johnson & Johnson, 2009), the latter was excluded from the investigation as a distinctive analysis was practically impossible. Specifically, from a practical point of view, individual accountability can be structured, for instance, by testing each student individually or by having each student contribute different learning content for their learning companions (see Johnson, Johnson, & Smith, 2007), which automatically results in social interdependence. Secondly, the impact of these elements on different measures of successful learning interactions (e.g., learning performance, intrinsic motivation, appreciation of the learning companion) was assessed.

In addition to considering people's acceptance of educational robots and cooperative learning as a strategy to effectively shape HRI for learning purposes, it is crucial to take into account educational robot design characteristics when pursuing a successful introduction of

robots into education. The third research focus addresses the question of how to design educational robots to meet users' expectations as will be described in the following.

1.4 Educational Robot Design

Considering the design issue is particularly important as research investigating how robot design affects people's perception and acceptance of robots clearly suggests that the context plays an important role and indicates that a robot's appearance should be adapted, depending on its application context (Duffy, 2003). To illustrate, it was found that people preferred robot companions used in home settings to have a more humanlike appearance and human attributes (Walters, Syrdal, Dautenhahn, Te Boekhorst, & Koay, 2008) as well as an extrovert and agreeable personality (Walters, Koay, Syrdal, Dautenhahn, & Te Boekhorst, 2009). In contrast, in the context of a medical examination, a very humanlike robot appearance led to feelings of embarrassment (Bartneck, Bleeker, Bun, Fens, & Riet, 2010). Similarly, in a verbal interaction scenario, it was observed that a machinelike robot was perceived to be more trustworthy and empathic than a very humanlike robot (Złotowski, Sumioka, Nishio, Glas, Bartneck, & Ishiguro, 2016).

In line with this, research carried out in educational settings has shown that different users have distinct needs and expectations regarding the appearance and capabilities of educational robots: Woods, Dautenhahn, and Schulz (2004) evaluated fifth grade school students' preferences for robot design, and found that children evaluated humanlike robots with obvious mechanical features most positively. In contrast, more recent work indicated that elementary school students favored animal-like robots with overstated facial features (Oros, Nikolic, Borovac, & Jerkovic, 2014). A study conducted with interaction designers and elementary school children demonstrated that while interaction designers envisioned small animal- or cartoon-like robots with facial features, children again preferred a humanlike robot with clear robotic features, such as a screen, sensors, or robotic hands (Obaid, Barendregt, Alves-Oliveira,

Paiva, & Fjeld, 2015). At the same time, children's perceptions varied as a function of previous robot experience: Children with prior experience of robots favored smaller, machinelike robots, while those children without prior experience envisaged bigger, humanlike robots (Obaid, Barendregt, et al., 2015). A robot design toolkit was developed and evaluated in a follow-up study (Obaid, Yantaç, Barendregt, Kırlangıç, & Göksun, 2016). The results showed that children favored a rather humanlike appearance with robotic characteristics like mechanical arms or a metallic surface, thus confirming the previous findings. In addition, children stated that their ideal educational robot should have a storage compartment for school materials, a screen on its torso, and a button to turn it off (Obaid, Yantaç, et al., 2016).

Taken together, the findings imply that preferences depend on person- and context-specific factors, and that the way in which people perceive robots can affect the likelihood of them being integrated into everyday environments, such as education. Thus, by evaluating future end users' preferences for educational robot design, this thesis provides significant implications for designing robots which meet students' expectations and requirements.

2   PRESENT RESEARCH

Researchers from different domains are attempting to progressively substantiate the rather new research domain of social HRI in education. The present work aims to contribute to this growing research field by scrutinizing the acceptance and applicability of social robots in educational contexts. More specifically, it has the overarching objective of identifying and evaluating factors which could contribute to the successful introduction of educational robots into learning environments. For this purpose, eight empirical studies were conducted which were guided by the following three research questions:

RQ1   *Will people accept educational robots for their learning and teaching?*

As technology acceptance is an important factor contributing to the success or failure of technology usage, it can reasonably be assumed that future stakeholders' acceptance of educational robots will determine their future use in education. Thus, people's attitudes toward educational robots and ways of improving them must be examined. Three empirical studies were conducted for this purpose. The first study (Reich-Stiebert & Eyssel, 2015) investigated university students' attitudes toward learning with educational robots in higher education. It demonstrated that German undergraduates have a rather neutral attitude toward learning with robots. To complete the picture, the second study (Reich-Stiebert & Eyssel, 2016) assessed German school teachers' attitudes toward teaching with robots. Interestingly, teachers reported rather negative attitudes toward educational robots. To tackle people's reluctance toward educational robots, a strategy to improve people's attitudes by having them participate in an educational robot's visual prototyping process was introduced in the third study (Reich-Stiebert & Eyssel, 2019). The findings indicate that user involvement increases robot acceptance and reduces educational robot anxiety.

RQ2 *Is it possible to implement cooperative learning elements in HRI and can they contribute to facilitating HRI in learning settings?*

The second research question focused on how to effectively design HRI for learning purposes by building upon the cooperative learning paradigm. Given that people are inclined to regard robots as social entities, it appears likely to create cooperative learning interactions between humans and robots. We draw upon educational literature on cooperative learning and report the few studies using theory-driven empirical methods to establish efficient learning interactions with robots. Studies four to seven (Reich-Stiebert & Eyssel, 2018) highlight those elements of cooperative learning which can be successfully implemented in HRI, and the way in which they affect the learning experience. Although the studies only provided limited statistically significant results, they include a critical reflection upon the usefulness of the approach for HRI and illustrate how future work can address the issues raised in the studies.

RQ3 *How should educational robots be designed to meet future end users' expectations and requirements?*

Finally, as a third focus, the present thesis addresses the question of how to design educational robots to meet users' expectations. People's perception and acceptance of robots vary depending on the context, thus emphasizing the importance of adjusting the robot's appearance to suit the application context. Consequently, it is necessary to draw upon end users' preferences for educational robot design to match their ideas and thereby increase the acceptance of educational robots. In the eighth study (Reich-Stiebert & Eyssel, revised and resubmitted), undergraduates' preferred robot design in terms of its physical appearance, interaction capabilities, display of emotion, and personality, is therefore evaluated.

Taken together, a series of empirical and experimental studies provide a solid basis for the current debate and for future research. Important insights that can contribute to the future use of educational robots are discussed.

2.1 Acceptance of Educational Robots

2.1.1 *Undergraduates' attitudes toward learning with educational robots*

To realize a successful implementation of robots in an educational setting, requires considering the attitudes of potential end users before robots are finally introduced in practice. Building on evidence from psychological research, which states that attitudes predict how individuals will treat an attitude object (e.g., Eagly & Chaiken, 1998; Fazio, 1990; Fazio & Roskos-Ewoldsen, 2005), it can be assumed that people's attitudes toward educational robots will determine the future acceptance of robots for learning and teaching. This is particularly important given that an individual's technology acceptance is a critical factor in constituting the success or failure of technology usage (e.g., Davis, 1989, 1993). However, to date, only a few studies have investigated people's attitudes toward educational robots (e.g., Choi, Lee, & Han, 2008; Han, Hyun, Kim, Cho, Kanda, & Nomura, 2009; Serholt & Barendregt, 2014; Serholt et al., 2014); in Germany, this has not been attempted at all. A central observation in the cited works was that people tend to be reluctant toward the application of educational robots, despite recognizing their potential benefit for learning and teaching (e.g., Choi, Lee, & Han, 2008; Han, Hyun, Kim, Cho, Kanda, & Nomura, 2009; Serholt et al., 2014).

To contribute to this area of research, we explored undergraduates' attitudes toward learning with robots, educational robot anxiety, and their contact intentions with respect to educational robots (Reich-Stiebert & Eyssel, 2015). In addition, the role of significant predictors of attitudes was examined, as well as which application potentials students envisaged for educational robots in terms of learning situations, role of educational robots, and use in

preferred subjects. Given the explorative nature of the study in the German context, no specific hypotheses were postulated for either attitudes toward educational robots or educational robots' preferred areas of application. Drawing on previous findings on factors influencing attitudes (e.g., European Commission, 2012; Kuo et al., 2009; Reich & Eyssel, 2013), it was assumed that demographic variables (i.e., age, gender, educational level), technical affinity, and need for cognition would significantly predict attitudes toward educational robots.

The results indicated that German university students had neutral attitudes toward educational robots, reported modest educational robot anxiety, and were hesitant about learning with an educational robot in the future. These findings might be explained by the fact that social robots are not yet common in the German context, particularly not in education. Therefore, promotional campaigns and the provision of information on educational robots would be an opportunity to familiarize students with educational robots.

In terms of predictors of robot acceptance, it was found that gender (women reported more negative attitudes and less willingness to interact with educational robots than men), age (younger participants reported significantly more negative attitudes and higher educational robot anxiety), and educational level (the higher participants' educational level, the less willing they were to learn with an educational robot) significantly predicted robot acceptance. Additionally, it was observed that attitudes improved, educational robot anxiety decreased, and the willingness to learn with educational robots in the future rose as a function of respondents' technical affinity. Finally, need for cognition was confirmed as a significant predictor of students' robot acceptance: More specifically, those respondents with a high need for cognition reported fewer negative attitudes and less educational robot anxiety. Although these factors were found to significantly predict students' attitudes toward educational robots, the consequence should not be to use educational robots preferably for male learners or technically interested students, for instance. Rather, attention should be paid to addressing different learners to ensure equal access to this new learning technology.

With regards to students' preferences for the application of educational robots, the majority would prefer educational robots to be applied in individual learning scenarios, followed by learning in groups. Only a few students could imagine using educational robots in the classroom community. Correspondingly, most students favored educational robots in the role as a tutor or teaching assistant, rather than as an independent teacher. Furthermore, students expected educational robots to be useful in STEM-related areas and less helpful in social sciences and humanities. As programmable robots like the Lego Mindstorms platform (The LEGO Group) are already used in these domains, this finding is not surprising. As a consequence, it would be possible to introduce robots primarily in STEM-related subjects, and afterwards extend their use to other, less technical fields.

2.1.2 *School teachers' attitudes toward teaching with educational robots*

To complement the picture of attitudes toward educational robots in the German context, the second study (Reich-Stiebert & Eyssel, 2016) evaluated school teachers' attitudes toward teaching with robots and took into account various school environments (i.e., elementary schools, secondary schools, and vocational schools). In addition, predictors of attitudes as well as teachers' readiness to use educational robots in various learning environments were studied.

Based on the previous findings (Reich-Stiebert & Eyssel, 2015), it was hypothesized that German school teachers would report rather negative attitudes toward educational robots and have little interest in using educational robots for future teaching. With respect to school type, it was anticipated that elementary school teachers would express more negative attitudes and less interest in future use than secondary or vocational school teachers. It was expected that demographic variables (i.e., age, gender), technical affinity, and teaching domain would be significant predictors of attitudes toward educational robots. Finally, it was predicted that teachers would prefer robots to be used as tutors or teaching assistants for individual or group

learning. Moreover, it was hypothesized that teachers would prefer to use robots in STEM-related domains.

As predicted, German school teachers reported quite negative attitudes toward teaching with educational robots. However, surprisingly, their willingness to use educational robots in the future was moderate. Elementary school teachers expressed more negative attitudes toward educational robots than secondary and vocational school teachers and were less interested in their future use. This trend is probably due to the limited distribution of educational robots in the German context. However, as teachers' attitudes are related to their willingness to use new technologies for their teaching (Teo, 2006), it appears crucial to facilitate attitude change toward educational robots to increase teachers' readiness to use robots for teaching purposes.

Technical affinity was the only predictor of teachers' attitudes and willingness to use educational robots. Finally, as had been expected, teachers envisaged using robots as tutors or teaching assistants for individual or group learning, but not for frontal teaching of an entire course. Therefore, when aiming at successfully introducing robots into education, it is important to emphasize their role as learning companions for individual learning activities that will not replace the function of human teachers in the classroom. Furthermore, school teachers preferred to apply educational robots in STEM-related domains, such as informatics, or physics, and rejected their use in social domains, like arts, or music. Therefore, as mentioned previously, it would be worthwhile to promote the use of educational robots beyond technical domains.

A qualitative content analysis of two open-ended questions on teachers' expectations and concerns regarding the application of educational robots, indicated that teachers expected robots to create a motivating environment, serve as a source of information for students, assess and monitor students' learning status, provide individual support for under-achieving students, and be easily usable. As their concerns, teachers mentioned that robots could be a disruptive factor, and feared students' loss of interest over time, additional workloads, and high acquisition costs, as well as the replacement of both interpersonal relationships and the teachers themselves.

Taken together, teachers' attitudes toward educational robots were found to be rather negative and their willingness to use robots for teaching was limited, which clearly implies that their expectations and concerns must be taken seriously when attempting a successful introduction of robots into education.

2.1.3   Changing attitudes toward educational robots

The results of the first two studies demonstrated that students' and teachers' attitudes toward educational robots are, respectively, moderate and even negative. Moreover, both students and teachers are rather unwilling to use robots for educational purposes (Reich-Stiebert & Eyssel, 2015, 2016). Nonetheless, as social robots progressively enter educational environments (International Federation of Robotics, 2017), people's negative views could be a serious obstacle to prolific robot deployment. One way of addressing this problem might be to change people's attitudes toward educational robots, thus increasing their acceptance of learning with them. This immediately raises the question of how to change attitudes toward robots. Collaborative design provides a valuable opportunity: That is, research findings have emphasized that user involvement in a design process had a positive effect on people's attitude toward the design object and their inclination to use it (e.g., Franke, Keinz, & Steger, 2009; Franke, Schreier, & Kaiser, 2010; Norton, Mochon, & Ariely, 2012; Randall, Terwiesch, & Ulrich, 2007).

By applying these outcomes to the identified problem, it was assumed that user involvement in a robot design process could positively affect the end users' attitudes toward educational robots. More precisely, it was hypothesized that a higher degree of participation (no vs. low vs. high participation) in the prototyping process of an educational robot, would lead to more positive attitudes, less educational robot anxiety, and greater willingness to learn with and to possess an educational robot. To examine this research question, end users were actively involved in an educational robot's prototyping process (Reich-Stiebert & Eyssel,

2019). Three factor levels were implemented (no vs. low vs. high participation in the prototyping process) in a single factor between-subjects design. In the no participation condition, participants evaluated the design of a NAO robot (SoftBank Robotics), which is one of the robots most commonly used in education and research. In the low and high participation conditions, respondents had to indicate their preferred educational robot design by choosing between different characteristics for appearance (e.g., preferred gender, head shape, colors, or facial features), interaction (e.g., via speech, facial expressions, gestures), personality (e.g., identification and adaption to human personality traits), and emotion (e.g., recognition and display of basic emotions). To avoid mere exposure and mere thought effects that can potentially positively bias attitudes (e.g., Clarkson, Tormala, & Leone, 2011; Tesser & Conlee, 1975; Zajonc, 1986), the contents and time for evaluating the educational robot features were kept constant across all the experimental conditions. Therefore, participants were presented with 30 questions with similar content for each condition.

As expected, a positive effect was found for user participation on attitudes. The findings demonstrated that participation resulted in more positive attitudes toward educational robots in general, and a reduction in educational robot anxiety. However, no significant effect was found from user participation on students' behavioral intentions. Regardless of the degree of participation in the robot prototyping process, undergraduates were equally willing to own and learn with an educational robot. Although the trend in the data suggests that the manipulation of participation in the robot prototyping process had a positive effect on students' willingness to possess an educational robot, it might not have been strong enough to influence their behavioral intentions. It is likely that the results were weakened by the lack of statistical power and that increasing the statistical power would enhance the effect of the manipulation. With regard to the content, this assumption can be attributed to the fact that participants had no actual tangible outcome after having composed their ideal educational robot. Indeed, participants did not see a final image of the robot they had created. Therefore, they probably had no clear notion

of what it actually looked like and could not really imagine learning with such a robot. The work by Norton and colleagues (2012) provides support for this reasoning. They found that the successful completion of a work process is a critical determinant of people's appreciation for the final product and their willingness to purchase it.

Overall, the present results support the idea that involving end users in a robot prototyping process may contribute to a smoother introduction of robots into educational contexts. It was possible to demonstrate that simple user involvement in the initial phase of a design process was enough to improve their attitudes toward educational robots and reduce educational robot anxiety. Accordingly, it is likely that greater involvement during the design process by means of mutual communication and exchange between users, designers, and researchers, could prove even more efficient in shaping future users' acceptance of educational robots.

2.2 Cooperative Learning with Educational Robots

In the context of the future introduction of robots into education, it has been shown that students' and teachers' acceptance of educational robots is rather moderate. However, the research has also indicated a way of positively affecting end users' attitudes toward educational robots, thereby helping to facilitate their future introduction into education. However, with regard to actual learning activities with robots, the question of how to shape human-robot learning interactions effectively, arises. This research attempts to pursue this pivotal question by drawing on the well-established educational practice of cooperative learning. While a number of previous studies have already focused on cooperative learning activities between humans and robots (e.g., Jerčić, Wen, Hagelbäck, & Sundstedt, 2018; Plauska & Damaševičius, 2014; Ushida, 2010), only scant attention has been paid to sophisticated theories about inducing cooperative human-robot learning. A frequently-used approach for promoting cooperative learning between humans and robots is the learning-by-teaching paradigm, which has been proven to improve learning performance and engagement (e.g., Chandra, Alves-Oliveira,

Lemaignan, Sequeira, Paiva, & Dillenbourg, 2015; Lemaignan, Jacq, Hood, Garcia, Paiva, & Dillenbourg, 2016; Tanaka & Matsuzoe, 2012). Nevertheless, these studies cover only a small range of methods for designing cooperative learning activities. In addition, HRI research has been encouraged to adopt multidisciplinary approaches and theory-driven perspectives when facing questions relating to the usage of social robots (e.g., Alimisis, 2012; Eyssel, 2016).

Therefore, the present work has sought to provide another approach to cooperative learning interactions between a human and a robot. The theoretical framework underpinning this endeavor is based on the essential elements of cooperative learning as proposed by Johnson and Johnson (1994, 2009). The elements of cooperative learning in HRI have been systematically evaluated by the application of theoretically substantiated experimental designs, following recommendations proposed by Alimisis (2013).

2.2.1 *Social interdependence in human-robot learning*

The first principle of cooperative learning is social interdependence between learners. Such a feeling can be achieved when individuals recognize that their learning outcomes are affected by both their own and their group members' efforts (Johnson & Johnson, 2009). To date, the implementation of social interdependence in educational interaction scenarios has not been sufficiently investigated in the context of HRI. Only a few studies have touched on this concept: As an illustration, Leite, Martinho, Pereira, and Paiva (2009) examined the social presence of robots in a long-term study and assessed, inter alia, affective and behavioral interdependence, two subdimensions of social presence, between children and a robot. Surprisingly, affective interdependence (the extent to which two people's emotional and attitudinal states affect each other) and behavioral interdependence (the extent to which two people's behaviors affect each other) both decreased over time. The authors argue that the robot was perceived less as being a companion but rather more like an independent interface. In a study, which examined the impact of social distance on people's responses to robots, interdependent versus independent

task goals were induced, among other aspects. Participants were either asked to work interdependently with a robot to attain a given goal, or to achieve the goal independently of the robot. Once again, no differences were found between the inter- and independent conditions. Due to these outcomes, the nature of social interdependence between humans and robots in social settings, such as learning interactions, remains unclear.

To shed light on this issue, the third study explored whether people are aware of social interdependence with an educational robot in the first place, and how this affected the learning interaction (Reich-Stiebert & Eyssel, 2018). Drawing upon educational research on social interdependence, it was predicted that participants in the socially interdependent learning condition would have better learning outcomes, would report a more positive affective state, and would evaluate the robot more positively, compared to those in the socially independent learning condition. Dependency in the learning interaction was manipulated by referring back to resource, reward, and goal interdependence, which have been shown to induce positive interdependence (see Deutsch, 1962; Johnson & Johnson, 1994; Slavin, 1996).

Unexpectedly, no difference between the socially interdependent and independent conditions was found. The overall high averages for social interdependence indicated that in both learning interactions participants perceived the robot as being rather interdependent. As a consequence, further analyses also did not reveal significant effects of the learning interaction on the dependent measures. It should be pointed out that implementing an explicitly independent learning interaction (without simultaneously implying a competitive atmosphere) is very difficult. In both conditions, for instance, participants provided new ROILA vocabulary, thus making the robot dependent on them. Otherwise no interaction with the robot would have been necessary. The common practice of reimbursing participants also represents a kind of reward. Interestingly, though, it was observed that social interdependence was positively correlated with the dependent measures. Consequently, perceiving a human-robot learning

interaction as more interdependent, seems to contribute to higher intrinsic motivation, a better learning mood, higher self-efficacy, and a more positive evaluation of the robot.

It is necessary to clarify which factors clearly induce social interdependence between human learners and educational robots, and whether interdependence with an educational robot generally leads to a more positive learning experience. To do so, future work should focus on the *degree of interdependence* (Kelley, Kerr, Reis, Holmes, Rusbult, & van Lange, 2003). Future studies should develop strategies for inducing high interdependence, namely, situations in which one individual's outcomes are highly dependent on those of another individual. Although interdependence was manipulated on three levels (i.e., task, goal, and reward interdependence), it is necessary to understand which of these factors was essential for establishing an interdependent learning interaction between the human and the robot, or whether completely different factors are required. In addition, the potentially mediating role of individual accountability, an element of cooperative learning strongly interlinked with social interdependence, should also be investigated in future work.

2.2.2 *Face-to-face interaction in human-robot learning*

The second study in this framework was devoted to face-to-face interaction in cooperative learning (Reich-Stiebert & Eyssel, 2018). Direct face-to-face interaction has proven essential for successful cooperation between learners (Johnson & Johnson, 2009). The *media naturalness theory* (Kock, 2004) underpins the effectiveness of face-to-face interaction by postulating that this type of communication is the most effective strategy for exchanging information. This theory applies evolutionary assumptions to substantiate which form of communication media simulates human communication characteristics most closely. According to this theory, the human brain has been developed for co-located communication, including face-to-face interaction (Kock, 2004; Kock & Hantula, 2005). This reasoning prompts the question, whether the transition to technology-mediated learning, accompanied by the rise of virtual agents as new

interactants, counters effective learning activities. Norman's assumptions (1988) on the higher affordance emanating from physical objects and entities substantiates this viewpoint. To follow Norman's argument (1988), a physically tangible robot can give clearer indications of how it is to be used and interacted with than a virtual character. This issue is particularly important in the context of the prospective introduction and proliferation of robots in educational environments. Thus, we sought to explore the differences of direct interaction with a physically or a virtually embodied robot in the present study. This was based on a number of studies comparing the effectiveness of embodiment in human-robot learning interactions. Those studies, though, showed inconsistent results. While earlier studies demonstrated that interacting with a physically present robot led to increased learning gains and a more positive evaluation of the robot, compared to learning with the virtual representation of the robot (e.g., Kose-Bagci, Ferrari, Dautenhahn, Syrdal, & Nehaniv, 2009; Leyzberg et al., 2012), more recent studies did not confirm these findings (e.g., Kennedy, Baxter, & Belpaeme, 2015a; Rosenthal-von der Pütten, Straßmann, & Krämer, 2016).

An attempt was made to address these inconsistent findings and evaluate participants' affective state, which had not previously been considered (Reich-Stiebert & Eyssel, 2018). It was hypothesized that participants who interacted with a physically embodied robot would have better learning outcomes, report a more positive affective state, and evaluate the robot more positively compared to participants who had interacted with the virtual counterpart.

As predicted, participants in the physical embodiment condition perceived the robot to be more socially present than those in the virtual embodiment condition. Specifically, participants felt more socially connected to and involved with the real robot. Furthermore, a statistically significant difference was found between the conditions in terms of the learning outcomes, affective state, and the evaluation of the robot. In particular, participants who had learned with the physically embodied robot reported higher intrinsic motivation, perceived the robot as being warmer and more competent, and ascribed a higher educational impact to the robot than

participants who had learned with the virtually embodied robot. In contrast, participants in the physical embodiment condition had a lower learning performance than participants in the virtual embodiment condition. This outcome may be due to the novelty effect discussed in previous research (e.g., Kennedy et al., 2015a; Rosenthal-von der Pütten et al., 2016): The robot, as a novel technology, probably attracted participants' attention and distracted them from the learning content. In contrast, the novelty effect has also been used to explain results in favor of a physical robot embodiment's impact on learning (e.g., Leyzberg et al., 2012). Therefore, this interpretation should be handled cautiously. Future work is needed to clarify whether and how a robot's novelty affects learning, and whether this effect disappears during long-term interactions.

We conclude that a robot's physical presence in a learning interaction positively affects the learners' motivational state and their evaluation of the robot. Whether a robot's novelty actually influences learning and, if so, whether this effect disappears during repetitive interactions, has yet to be clarified. Long-term studies that focus on familiarizing participants with educational robots can help drawing conclusions about this issue. Taken together, the findings support the meaningfulness of direct face-to-face interactions in cooperative learning interactions between a human and a robot.

2.2.3   *Social support in human-robot learning*

In the previous two studies, it was discovered that while the role of social interdependence in HRI remains unclear, direct face-to-face interaction with a real robot improves students' intrinsic motivation and their perception of the robot. In the third study, the influence of social support on human-robot learning was examined (Reich-Stiebert & Eyssel, 2018). The appropriate use of social skills, such as providing social support in cooperative learning interactions, has been demonstrated to play a key role in student retention and learning success (e.g., DeBerard, Spielmans, & Julka, 2004; Grillo & Leist, 2013; Tinto, 1997). HRI research

has similarly benefitted from implementing social support in robot-mediated learning by using, for instance, facial expressions and gestures, social dialogue, or emotional support (e.g., Leite, Castellano, Pereira, Martinho, & Paiva, 2014; Lubold, Walker, Pon-Barry, & Ogan, 2018; Searbeck et al., 2010). Increased learning outcomes (e.g., Lubold et al., 2018; Saerbeck et al., 2010), higher intrinsic motivation (e.g., Saerbeck et al., 2010), or more socially engaging behaviors toward a robot (e.g., Serholt & Barendregt, 2016) have all been attributed to the positive effects of social support offered by a robot. Although social support has already been considered in HRI, previous works have only focused on elementary school children as the target group, and only made limited reference to the theoretical principles of social support. The present study addressed these issues by drawing on the theory of student academic support in higher education (Mazer, 2008). This theory indicates that undergraduates utilize informational (e.g., providing useful information), esteem-raising (e.g., increasing others' self-esteem), motivational (e.g., motivating others to study), and venting (e.g., listening to students venting about classes or teachers) strategies to support each other (Mazer, 2008; Thompson & Mazer, 2009a). In our HRI setup, a robot provided student academic support to undergraduates on the motivational, esteem-raising, and venting level. Informational support was not considered as this would have meant withholding information or learning content in the control condition, making learning impossible. More precisely, the robot encouraged students to learn (i.e., motivational support), acknowledged participants' efforts (i.e., esteem support), and admitted that other students had experienced similar frustrations during their learning interaction (i.e., venting support).

It was predicted that participants in the socially supportive condition would have better learning outcomes, report a more positive affective state, and evaluate the robot more positively compared to those in the neutral, non-supportive condition.

As expected, participants in the social support condition perceived the robot to be more socially supportive than those in the neutral condition. Moreover, it was found that social

support was positively correlated with the dependent measures: Perceiving a robot to be highly supportive led to a more positive affective state and a better evaluation of the robot. Surprisingly, however, further analyses did not show any statistically significant differences between the two groups.

It might be assumed that the informational support, which was applied in both conditions to provide participants with the learning content, plays a key role across the four dimensions of student academic support in HRI and is probably sufficient to create the impression of a supportive robot. This assumption is in line with findings from educational psychological research, which showed that informational support has a higher priority than esteem-raising and motivational support (Thompson & Mazer, 2009b). It was also observed that a close relationship between learners and a shared context facilitated the exchange of academic support (e.g., Thompson, 2008; Thompson & Mazer, 2009b). In the context of HRI, this could represent a substantial barrier to the efficient implementation of the four dimensions of student academic support. An educational robot, which can share a common experience and has a close relationship with the human learner, is far from being reality. However, this is probably the appropriate way to implement social support in HRI for higher education. Namely, educational robots which, first and foremost, assist in learning activities by providing informational support, while also inviting students to complement and acknowledge each others' efforts, encourage each other, and listen to their classmates' venting. Future studies focusing on multiparty interactions between learners and a robot are needed to clarify this concept.

2.2.4   *Group processing in human-robot learning*

To close the circle, the fourth study in the context of cooperative learning in HRI focused on group processing (Reich-Stiebert & Eyssel, 2018). From an educational viewpoint, group processing is a strategy in which learners regularly reflect on how they can improve the learning process (see Johnson, Johnson, & Smith, 2007). Specifically, it involves feedback which helps

learners to decide which behaviors have been helpful for achieving the learning goals and which should be changed in order to pursue the goals (e.g., Johnson, Johnson, & Smith, 2007; Yager, Johnson, Johnson, & Snider, 1986). In the context of HRI, only a few studies have sought to investigate the effectiveness of verbal feedback in learning interactions. Additionally, these works have been predominantly restricted to a robot providing feedback on the learning content, but not on the learning process per se. Moreover, drawing conclusions about the impact of verbal feedback on human learning is complicated by the fact that inherently different feedback strategies have been used. To illustrate, it was found that participants preferred a robot to offer positive or neutral feedback instead of negative feedback, and in turn evaluated the robot more positively when it provided the desired positive or neutral feedback (e.g., Park, Kim, & del Pobil, 2011). Schneider, Riether, Berger, and Kummert (2014) compared motivational feedback and task performance related feedback provided by a socially assistive robot. The task performance related feedback was found to elicit better task performance and a more positive evaluation of the task. A recent study that explored whether encouraging or challenging feedback offered by a robot was more effective, indicated that both types of feedback resulted in higher task performance and task engagement (Tsiakas, Abujelala, & Makedon, 2018).

The reflection of HRI in a learning setting has not yet been explored, and research that implements sound theoretical concepts of feedback in HRI is also lacking. To tackle these issues, the present study incorporated group processing into HRI. In fact, participants and the robot provided mutual feedback on the learning process in two consecutive interactions. The primary objective was to decide which behaviors were helpful and which should be changed in the second learning interaction. In order to provide effective feedback, a feedback model proposed by Hattie and Timperley (2007), which operates on different levels and was developed to enhance learning, was used: Feedback was involved on the task performance level (i.e., correcting incorrect answers and provide additional information), the process level (i.e., developing further learning strategies), and the personal level (i.e., positive evaluations about

the student, and their learning efforts). Participants' feedback was also incorporated into the robot's behavior for the second learning session.

It was assumed that participants in the group processing condition would have better learning outcomes, report a more positive affective state, and evaluate the robot more positively compared to those in the control condition without feedback. In addition, it was expected that there would be an improvement with respect to the evaluation of the dependent measures in the experimental condition over time.

In general, participants evaluated the feedback session positively, and their commitment to adopting the robot's feedback for the second learning session was rather high. Concerning the different levels of feedback, no changes on the self-level were preferred. That is, no participant requested the robot to change the number of motivational statements or amount of praise. Almost three quarters of the participants asked the robot to offer additional information on the learning content (i.e., task performance level). On the process level, about 60 percent favored including visual learning by offering learning cards with written explanations and a vocabulary list. Interestingly, a similar pattern has been observed in educational psychological literature: Feedback on the correctness of responses and effective learning strategies was found to be more effective than praise that had limited relevance to the learning content or the process per se (see Hattie & Timperley, 2007). With respect to the present study's hypotheses, the results did not demonstrate a significant change in the dependent measures over time. Similarly, there was no difference between the conditions with respect to participants' learning performance, affective state, or evaluation of the robot, nor was there any interaction between time and condition. In contrast, feedback was positively correlated with the dependent measures, indicating that a positive evaluation of the feedback session led to a more positive affective state and to a more positive evaluation of the robot.

However, since these outcomes contradicted the previous findings which emphasized a positive effect on learning from feedback (e.g., Park et al., 2011; Schneider et al., 2014; Tsiakas

et al., 2018), we admit that the rather artificial nature of the learning setup might have adversely affected both the perception of the interaction and the robot evaluation. In fact, learning an artificial robot language had no relevance for students. Further, the learning content was rather simple (i.e., participants had to learn a few ROILA words and basic grammar). It can be assumed that the provision of feedback on such simple learning tasks did not affect participants' learning behavior as it would have when participants had to learn more demanding educational content. In addition, despite the fact that it was evaluated positively, the provision of feedback to reach an externally-assigned goal seemed rather ineffective. Consequently, future research should focus on investigating the effectiveness of process-oriented feedback, in real learning activities that are more challenging and cognitively demanding in nature, taking place in actual learning settings, such as lectures or classrooms. Finally, we argue that the predefined feedback opportunities might also have reduced the possible effect of feedback on the learning experience. We predefined the feedback possibilities on the task, process, and self-level to ensure an effective implementation of participants' feedback into the robots' behavior. Therefore, considerably more work is needed to develop educational robots that are capable of autonomously comprehending learners' spontaneous feedback and implementing it into their future learning behavior according to learners' requirements.

2.3 Educational Robot Design

After having clarified the questions of robot acceptance and the meaningfulness of cooperative learning for HRI in higher education, the issue of the ideal educational robot design for the university context remains to be tackled. In fact, an increasing interest in educational robot design has emerged in recent years (e.g., Obaid et al., 2015, 2016; Oros, Nikolić, Borovac, & Jerković, 2014; Woods, Dautenhahn, & Schulz, 2004). To summarize, the literature implies that person- and context-specific factors clearly determine preferences in educational robot design. Despite this, to date, no previous work has addressed undergraduates' design

preferences with respect to educational robots. However, university students constitute a core end user group for educational robots and should not be overlooked, bearing in mind that university education is particularly seeking to embed novel computer technologies as essential educational resources (e.g., Selwyn, 2007). Another noteworthy finding, which has been documented in previous work, indicates that end users hold an inherently distinctive role in the process of educational robot design: While some approaches have ascribed users a rather passive role as evaluators of robot platforms (e.g., Oros et al., 2014; Woods et al., 2004), others have actively involved potential end users contributing their needs and experiences (e.g., Obaid, Barendregt, et al., 2015; Obaid, Yantaç, et al., 2016). User-centered design, a methodology which is becoming increasingly important in HRI research (see Šabanović, 2010), espouses the latter role of end users.

Thus, with the help of user-centered design, the eighth study was conducted to provide an insight into university students' design preferences for educational robots (Reich-Stiebert & Eyssel, revised and resubmitted). More specifically, it aimed to involve undergraduates in the visual prototyping of a robot which could serve as a personal learning companion across different disciplines and for different student groups. In doing so, the study benefitted from the key features of prototyping, representing a simple and efficient procedure for creating early models of a product while actively involving users (Cerpa & Verner, 1996). We relied on various user-centered design models which had previously been applied in different fields (e.g., Paulovich, 2015; Sless, 2008; Vink, Imada, & Zink, 2008) for composing the user-centered design process. After reading a short description of educational robots' features and functions, respondents had to indicate their preferred educational robot design. More specifically, respondents could choose between different characteristics for the aspects appearance, interaction, personality, and emotion (derived from Woods, Dautenhahn, Schulz, 2004).

Overall, the findings demonstrated that university students preferred a medium-sized (100 to 150 cm) robot with a rather machinelike appearance and a few human characteristics (e.g.,

head, hands, facial features; see Fig. 1). In addition, the majority of undergraduates stated that educational robots should be gender-neutral. This observation is related to recent findings showing that robot gender plays a minor role in human-robot learning activities (Reich-Stiebert & Eyssel, 2017). For interactions, almost all participants preferred natural interaction via speech, but they also mentioned that the robot should be equipped with a tablet for illustrating explanations or gathering information. The results further suggest that a robot should be able to display
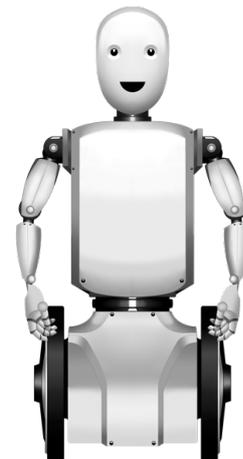
Figure 1. Visual prototype of an ideal educational robot from university students' view.

basic, positive emotions. Moreover, it was found that the ideal educational robot should behave conscientiously, agreeably, and openly, which is not surprising as these traits have been found to be positively related to successful learning (e.g., Komarraju, Karau, Schmeck, & Avdic, 2011; Verešová, 2015). To support the quantitative data, a qualitative content analysis was conducted using an open-ended question to explore which additional characteristics and features students' ideal educational robot should have. It was possible to confirm that students had no preference for an excessively humanlike robot appearance. Additionally, the university students emphasized privacy and security issues by mentioning that an educational robot should not be capable of harming people, be simple to handle, and easy to shut off at any time.

In its entirety, the present study emphasizes the importance of involving undergraduates in the design processes for educational robots. It was possible to show that university students have concrete requirements for educational robot design. It can be reasonably assumed that by meeting the future end users' needs and expectations, a contribution can be made to the future acceptance of such robots.

3 GENERAL DISCUSSION

The primary and overarching objective of the present dissertation was to examine the acceptance and applicability of social robots in educational contexts. To that end, factors which contribute to the future introduction of social robots into education were evaluated on three levels: The acceptance of educational robots, effective design of HRI for learning purposes by building upon the cooperative learning paradigm, and educational robot design. In fact, critical aspects were observed which could help to facilitate the implementation of robots into educational settings. Figure 2 provides a comprehensive overview of the resulting factors:
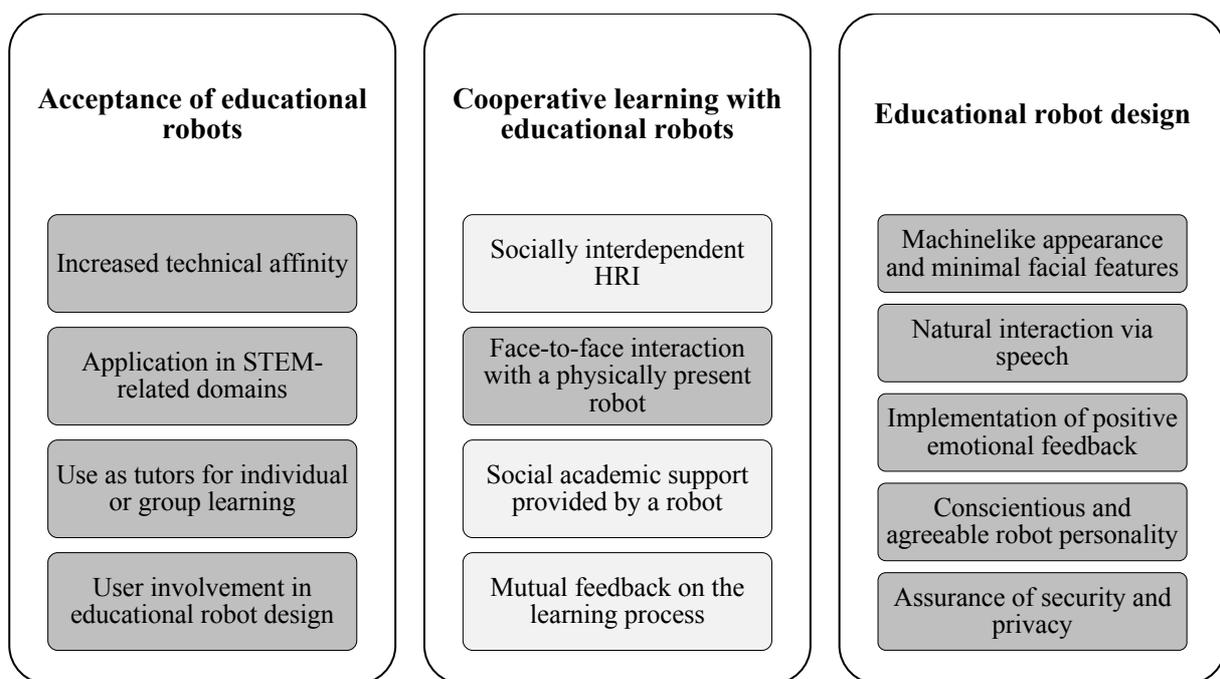
Figure 2. Factors which contribute to a successful introduction of social robots into education. The lighter boxes indicate factors which have not been clearly proven to be effective.

In terms of future stakeholders' acceptance of educational robots, one major factor was identified which was positively associated with people's attitudes toward educational robots: Technical affinity (Reich-Stiebert & Eyssel, 2015, 2016). One potential for increasing people's acceptance of educational robots might therefore consist in increasing people's overall interest

in technology, for instance, by offering more technical training opportunities in schools and universities. Associated with this, we observed that students and teachers preferred to use educational robots in STEM-related subjects, rather than in other subjects. As a result, educational robots could be initially introduced in these domains and their application could be extended to other less technical fields, such as history or music, once students have become accustomed to them. Nevertheless, campaigning for the application of educational robots in social and cultural subjects to demonstrate their broad potential would also be worthwhile. In addition, students and teachers envision using robots as tutors or teaching assistants for individual or small-group learning activities. Therefore, instead of one single robot, multiple educational robots should be applied in classrooms and lectures to increase the end users' willingness to learn and teach with them. Finally, user involvement in the robot design process has proven to be another possibility for accelerating future end users' acceptance of educational robots (Reich-Stiebert & Eyssel, 2019). Clearly, attitudes toward robots improved and robot anxiety reduced by involving students in the earliest stages of a robot's design process, thereby contributing to a smoother introduction of robots into educational contexts.

With regard to the second research focus, it was discovered that although the approach of cooperative learning is mainly practicable for HRI, its effectiveness for students' learning has not been proven conclusively (Reich-Stiebert & Eyssel, 2018). In relation to applicability, it could be demonstrated that students perceived a stronger social presence from a physically embodied robot in a face-to-face interaction. Furthermore, participants acknowledged the social support offered by the educational robot and appreciated the provision of feedback on the learning process. It proved difficult, though, to perceive social interdependence with a robot. Given that the dependence manipulation was sounder than others which have been applied in HRI and HCI (e.g., Kim & Mutlu, 2014; Nass, Fogg, & Moon, 1996), which was also confirmed by a successful pretest, we do not believe that the manipulation was too weak. On the contrary, we suppose that a clear differentiation between inter- and independence was impeded by the

general setup of the HRI in the study. It is common knowledge that humans are inclined to interact with communication technologies in a similar way to how they interact with humans (Reeves & Nass, 1996). More importantly, the use of verbal and visual social cues in communication technologies can foster the development of a social partnership (Moreno, Meyer, Spires, & Lester, 2001). In relation to the HRI in the fourth study, the robot could be regarded as a social actor, which probably triggered the feeling of a social partnership with it, and thereby resulted in both interactions being perceived as being rather interdependent.

Uncertainty about the effectiveness of cooperative learning in HRI still exists, due to the limited evidence obtained in the study. We clearly demonstrated the benefits of educational robots' physical presence in learning environments. First, participants were more inclined to interact with the robot. Second, they evaluated the robot more positively when they interacted directly with it. Consequently, the physical presence of robots, as opposed to their virtual representation, could accelerate their future usage for supporting learning endeavors. Contrary to our expectations, positive interdependence, social support, and group processing in HRI did not significantly affect participants' learning. Although indications were found that these cooperative learning elements were positively related to students' affective states and their evaluation of the robot, no definite conclusions could be drawn about their usefulness for HRI. Nevertheless, we are convinced that cooperative learning could make a valuable contribution to HRI, if it is remembered that it is one of the most successful instructional practices in education (e.g., Johnson & Johnson, 2009; Johnson, Johnson, & Smith, 2007; Slavin, 1996). Therefore, a greater focus on real learning environments, actual learning content that adheres to the curriculum, and multi-party interactions with a robot could produce interesting findings which would probably account more effectively for the mechanisms of cooperative learning in HRI.

Finally, with respect to educational robot design, it has been documented that, depending on the context, a robot's design affects people's perception and acceptance of it (e.g., Bartneck

et al., 2010; Duffy, 2003; Walters et al., 2008). In order to contribute to the future acceptance of educational robots, potential end users were involved in the visual prototyping process of an educational robot for higher education (Reich-Stiebert & Eyssel, revised and resubmitted). Undergraduates preferred a rather machinelike appearance with some humanlike characteristics, such as minimal facial features. To facilitate the interaction with an educational robot, it should preferably interact using speech, which is probably the most natural and simplest form of interaction for humans. Useful positive emotional feedback rather than a wide range of emotional responses, as well as robot behavior characterized by conscientiousness, agreeableness, and openness, were also deemed appropriate. Ultimately, to preserve people's sense of privacy and security, the robot's design has to guarantee that it can be easily handled and controlled simply.

If robotics research would not only pursue the goal of designing robots and investigating HRI for their own sake, but also aim to create robot platforms and HRI models for the benefit of future users, it would make an important step toward increasing people's readiness to accept and apply robots in educational environments. The results offered in the present work have provided useful indications on this matter. Considering the present outcomes for the future introduction of educational robots will contribute to increase their acceptance for learning and teaching activities as they give important insights into how to suit future end users' expectations and requirements in terms of educational robots' features and functions. At the same time, however, it has to be mentioned that the transition of robots into educational environments in which they can take over roles as teaching assistants and learning companions raises questions about the ethical and legal consequences, which will be discussed in the next section.

3.1 Ethical Considerations

Researchers have been prompted to face ethical issues from the very beginning of HRI research, thereby contributing to a culture of ethical awareness in robotics (see Riek & Howard,

2014). If one imagines that in future, students will learn and interact repeatedly with educational robots, it is plausible that they will perceive these robots to be social entities and build some kind of social relationship with them. As was observed in the second study that focused on school teachers' attitudes toward educational robots (Reich-Stiebert & Eyssel, 2016), school teachers were concerned about precisely this issue: Namely, that robots could replace interpersonal relationships between students and negatively affect students' social skills. In fact, the literature on robot ethics has already devoted a lot of attention to the replaceability question (e.g., Coeckelbergh, 2012; Decker, 2008). Therefore, HRI research is encouraged to consider humans' tendency to build social bonds to robots (e.g., Calo, 2010; Riek & Howard, 2014), and develop strategies for designing and using social robots which support learning activities while not inhibiting interhuman interactions. The idea of cooperative learning can make an important contribution to this aspect. As this approach focuses on how students should, ideally, interact with one another, HRI research can use cooperative learning principles as an orientation for a robots' behavior. However, clearly priority must be given to interactions between students. In particular, one potential direction could be to develop robot behaviors which guide cooperative interactions and teach students the skills they need to cooperate with each other effectively.

Another frequently highlighted area of concern relates to privacy aspects. Indeed, the results of the last study (Reich-Stiebert & Eyssel, revised and resubmitted) indicated that students emphasized privacy and security issues related to the use of educational robots. This is not surprising, if it is borne in mind that robots have the capabilities to sense and record their environment (Calo, 2010). With this capacity for accessing sensitive personal information, social robots contribute to blurring the line between private and public spaces (see Schulz & Herstad, 2017). As a consequence, HRI research is encouraged to develop strategies which contribute to securing students' and teachers' privacy and protect sensitive student data. Effective ways could be to increase transparency (i.e., people should be able to recognize when

a robot's sensors are activated or deactivated), and simplify operability (i.e., guaranteeing simple deactivation when it comes to sensitive and confidential issues).

Confronting these ethical and societal issues necessitates empirical research on human-robot learning interactions in natural educational settings. Therefore, in order to contribute to the successful introduction of robots into our educational system, the design principles for robotics and HRI must be thoroughly elaborated and properly implemented.

3.2 Conclusion and Outlook

Cutting-edge technologies are continuing to push education to new levels and, in consequence, research is facing the challenge of elaborating theoretical and practical approaches for a successful introduction of robots into education. However, as educational HRI is in its infancy, there is a lack of established theory and practice in this field. This thesis aimed to make an important contribution to the evaluation of the acceptance and applicability of educational robots by building on well-established theoretical assumptions. However, during this process, not only were obstacles which could hinder a successful implementation of robots into education encountered, but at the same time opportunities for countering these difficulties:

First and foremost, future stakeholders' attitudes toward educational robots proved to be moderate. More precisely, students and teachers were rather hesitant about the prospect of learning and teaching with robots (Reich-Stiebert & Eyssel, 2015, 2016). This reluctance could constitute a serious obstacle to the future use of educational robots. However, at the same time, factors such as people's high technical affinity, the application of robots in STEM-related domains, or the use of robots to support individual or small-group learning activities were determined which could positively affect end users' acceptance of educational robots.

In applying cooperative learning to learning with robots, an attempt has been made to adopt a well-established and successful pedagogical approach (Reich-Stiebert & Eyssel, 2018). Contrary to expectations, the results do not allow for a clear conclusion to be drawn about the

value of cooperative learning for HRI. Nevertheless, the unexpected outcomes also brought a noteworthy insight: The principles of cooperative learning in the sense of Johnson and Johnson (1994, 2009), probably cannot be directly translated to HRI. However, consideration should be given to using educational robots to strengthen cooperative learning strategies between students. It is emphasized that educational robots should not be considered to be learning partners equal to humans as they inherently lack reciprocity and mutuality (see Coeckelbergh, 2012; de Graaf, 2016). Instead, robots should be regarded as learning media which can contribute to guiding and supporting cooperative human-human interactions in learning environments. However, to address this issue, it is still necessary to clarify how cooperative learning practices can be productively implemented in HRI. One possibility would be to focus on user experience with educational robots. That is, evaluating students' experiences while cooperatively interacting and learning with robots. In doing so, future work can make a considerable contribution to discovering the factors which affect robot acceptance in social environments (see also Alenjung, Andreasson, Billing, Lindblom, & Lowe, 2017; Khan & Germak, 2018).

Finally, further impediments to people's acceptance of educational robots are associated with design-related issues. On the one hand, there is the risk relating to the violation of people's privacy and security. A possibility for confronting this risk could be to get people involved in robot design and take their concerns seriously. User-centered design approaches make it possible to collectively elaborate robot designs and interaction scenarios which meet users' requirements. In this way, end users could become familiar with robots and thereby could gain a feeling of control over them. On the other hand, one obstacle to the comprehensive distribution of educational robots are the prohibitive expenses inherent with these platforms, in terms of both the purchase and maintenance. Reducing the cost of purchasing educational robots will therefore be critical for their broad adoption in education. Moreover, researchers

and designers should consider developing easily manageable educational robots and reducing the workload involved with their introduction into learning and teaching activities.

Taken together, it cannot be denied that digitalization is going to affect education in the future. Software skills are increasingly essential in every field. Thus, education is more than ever being asked to cater for this development and recommend ways of purposefully using novel technologies for learning and teaching. The present work is expected to make a significant contribution toward providing a theory-driven and application-oriented footing for the purpose of applying robots in education. To be specific, this dissertation has evaluated factors, which contribute to the future introduction of educational robots, in a systematic manner. These factors were, for instance, the use of robots as tutors to support individual or small-group learning activities, direct face-to-face interaction with educational robots, the provision of social support by educational robots, or design requirements such as machinelike appearance, interaction via speech, or the display of positive emotions. Clearly, these factors should be taken into account when pursuing a successful implementation of robots into learning and teaching activities. However, the present work is only a starting point. The validity of its theories and the reliability of the proposed strategies for facilitating the deployment of robots in the education landscape must be further tested in laboratory and especially in field studies. It is hoped that this dissertation has featured both a sound basis and new incentives for further investigation into issues related to the implementation and application of educational robots which are intended to facilitate learning and teaching efforts in the future.

4   REFERENCES

Alarm in den Schulen: Die Computer kommen. (1984, November). *Der Spiegel*, pp. 97–129. Retrieved from http://www.spiegel.de/spiegel/print/d-13512161.html

Alenljung, B., Andreasson, R., Billing, E. A., Lindblom, J., & Lowe, R. (2017). User experience of conveying emotions by touch. *Proceedings of the 26th International Symposium on Robot and Human Interactive Communication* (RO-MAN 2017, Lisbon, Portugal), 1240–1247. doi: 10.1109/ROMAN.2017.8172463

Alimisis, D. (2012). Robotics in education & education in robotics: Shifting focus from technology to pedagogy. *Proceedings of the 3rd International Conference on Robotics in Education* (RiE 2012, Prague, Czech Republic), 7–14.

Bartneck, C., Bleeker, T., Bun, J., Fens, P., & Riet, L. (2010). The influence of robot anthropomorphism on the feelings of embarrassment when interacting with robots. *Journal of Behavioral Robotics, 1*(2), 1–7. doi: 10.2478/s13230-010-0011-3

Baxter, B., Kennedy, J., Senft, E., Lemaignan, S., & Belpaeme, T. (2016). From characterising three years of HRI to methodology and reporting recommendations. *Proceedings of the 11th International Conference on Human-Robot Interaction* (HRI 2016, Christchurch, New Zealand), 391–398. doi: 10.1109/HRI.2016.7451777

Benitti, F. B. V. (2012). Exploring the educational potential of robotics in schools: A systematic review. *Computers and Education, 58*(3), 978–988. doi:10.1016/j.compedu.2011.10.006

Burr, W. R., Mead, D. E., & Rollins, B. C. (1973). A model for the application of research findings by the educator and counselor: Research to theory to practice. *The Family Coordinator, 22*(3), 285–290.

Bravo, F. A., González, A. M., & González, E. (2017). Interactive drama with robots for teaching non-technical subjects. *Journal of Human-Robot Interaction, 6*(2), 48–69. doi: 10.5898/JHRI.6.2.Bravo

Calo, R. (2010). Robots and privacy. In P. Lin, G. Bekey, & K. Abney (Eds.), *Robot ethics: The ethical and social implications of robotics* (pp. 187–202). Cambridge: MIT Press.

Catlin, D., & Blamires, M. (2010). The principles of Educational Robotic Applications (ERA): A framework for understanding and developing educational robots and their activities. In J. Clayson & I. Kalaš (Eds.), *Constructionism 2010: Constructionist approaches to creative learning, thinking and education: Lessons for the 21st century* (pp. 1–17). Bratislava: Library and Publishing Centre, Faculty of Mathematics, Physics and Informatics, Comenius University.

Cerpa, N., & Verner, J. (1996). Prototyping: Some new results. *Information and Software Technology, 38*(12), 743–755. doi: 10.1016/0950-5849(96)01098-1

Chandra, S., Alves-Oliveira, P., Lemaignan, S., Sequeira, P., Paiva, A., & Dillenbourg, P. (2015). Can a child feel responsible for another in the presence of a robot in a collaborative learning activity? *Proceedings of the 24th International Symposium on Robot and Human Interactive Communication* (RO-MAN 2015, Kobe, Japan), 167–172. doi: 10.1109/ROMAN.2015.7333678

Choi, J., Lee, J., & Han, J. (2008). Comparison of cultural acceptability for educational robots between Europe and Korea. *Journal of Information Processing Systems, 4*(3), 97–102. doi: 10.3745/JIPS.2008.4.3.97

Clarkson, J. J., Tormala, Z. L., & Leone, C. (2011). A self-validation perspective on the mere thought effect. *Journal of Experimental Social Psychology, 47*(2), 449–454. doi: 10.1016/j.jesp.2010.12.003

Coeckelbergh, M. (2012). Care robots, virtual virtue, and the best possible life. In P. Brey, A. Briggle, & E. Spence (Eds.), *The good life in a technological age* (pp. 281–292). New York: Routledge.

Damaševičius, R., Narbutaitė, L., Plauska, I., & Blažauskas, T. (2017). Advances in the use of educational robots in project-based teaching. *TEM Journal, 6*(2), 342–348. doi: 10.18421/TEM62-20

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology: A comparison of two theoretical models. *MIS Quarterly, 13*(3), 319–340. doi: 10.2307/249008

Davis, F. D. (1993). User acceptance of information technology: System characteristics, user perceptions and behavioral impacts. *International Journal of Man-Machine Studies, 38*(3), 475–487. doi: 10.1006/imms.1993.1022

DeBerard, M. S., Spielmans, G. I., & Julka, D C. (2004). Predictors of academic achievement and retention among college freshmen: A longitudinal study. *College Student Journal, 38*(1), 66–80.

De Graaf, M. (2016). An ethical evaluation of human–robot relationships. *International Journal of Social Robotics, 8*(4), 589–598. doi: 10.1007/s12369-016-0368-5

Decker, M. (2008). Caregiving robots and ethical reflection: The perspective of interdisciplinary technology assessment. *AI & Society, 22*(3), 315–330. doi: 10.1007/s00146-007-0151-0

Duffy, B. R. (2003). Anthropomorphism and the social robot. *Robotics and Autonomous Systems, 42*(3–4), 177–190. doi: 10.1016/s0921-8890(02)00374-3

Eagly, A. H., & Chaiken, S. C. (1998). Attitude structure and function. In D. T. Gilbert, S. T. Fiske, & G. Lindzey (Eds.), *The handbook of social psychology* (pp. 269–322). New York: McGraw-Hill.

Eguchi, A. (2012). Educational robotics. Theories and practice: Tips for how to do it right. In B. S. Barker, G. Nugent, N., Grandgenett, & V. I. Adamchuck (Eds.), *Robots in K-12 education: A new technology for learning* (pp. 1–30). Hershey, Pennsylvania: IGI Global. doi: 10.4018/978-1-4666-0182-6

European Commission (2012). *Public attitudes towards robots* (Special Eurobarometer 382). Brussels: DG COMM. Retrieved from http://ec.europa.eu/commfrontoffice/public opinion/archives/ebs/ebs_382_en.pdf

Eyssel, F. (2016). An experimental psychological perspective on social robotics. *Robotics and Autonomous Systems, 87*, 363–371. doi: 10.1016/j.robot.2016.08.029

Fazio, R. H. (1990). Multiple processes by which attitudes guide behavior: The ODE model as an integrative framework. In M. P. Zanna (Ed.), *Advances in experimental social psychology* (pp. 75–109). San Diego: Academic Press.

Fazio, R. H., & Roskos-Ewoldsen, D. R. (2005). Acting as we feel: When and how attitudes guide behavior. In T. C. Brock & M. C. Green (Eds.), *Persuasion: Psychological insights and perspectives* (pp. 41–62). Thousand Oaks, US: Sage Publications.

Feil-Seifer, D., & Matarić, M. (2005). Defining socially assistive robotics. *Proceedings of the 9th International Conference on Rehabilitation Robotics* (ICORR 2005, Chicago, USA), 465–468. doi: 10.1109/ICORR.2005.1501143

Franke, N., Keinz, P., & Steger, C. J. (2009). Testing the value of customization: When do customers really prefer products tailored to their preferences? *Journal of Marketing, 73*(5), 103–121. doi: 10.1509/jmkg.73.5.103

Franke, N., Schreier, M., & Kaiser, U. (2010). The "I designed it myself" effect in mass customization. *Management Science, 56*(1), 125–140. doi: 10.1287/mnsc.1090.1077

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

Grillo, M. C., & Leist, C. W. (2013). Academic support as a predictor of retention to graduation: New insights on the role of tutoring, learning assistance, and supplemental instruction. *Journal of College Student Retention: Research, Theory & Practice, 15*(3), 387–408. doi: 10.2190/CS.15.3.e

Han, J., Hyun, E., Kim, M., Cho, H., Kanda, T., & Nomura, T. (2009). The cross-cultural acceptance of tutoring robots with augmented reality services. *International Journal of Digital Content Technology and its Applications, 3*(2), 95–102. doi: 10.4156/jdcta.vol3.issue2.han

International Federation of Robotics (2017). Executive Summary World Robotics 2017. Service Robots. Retrieved from https://ifr.org/downloads/press/Executive_Summary_WR_Service_Robots_2017_1.pdf

Jenkins, J. R., Antil, L. R., Wayne, S. K., & Vadasy, P. F. (2003). How cooperative learning works for special education and remedial students. *Exceptional Children, 69*(3), 279–292. doi: 10.1177/001440290306900302

Jerčić, P., Wen, W., Hagelbäck, J., & Sundstedt, V. (2018). The effect of emotions and social behavior on performance in a collaborative serious game between humans and autonomous robots. *International Journal of Social Robotics, 10*(1), 115–129. doi: 10.1007/s12369-017-0437-4

Johnson, D. W., & Johnson, R. T. (1989). *Cooperation and competition, theory and research.* Minneapolis: Interaction Book Company.

Johnson, R. T., & Johnson, D. W. (1994). An overview of cooperative learning. In J. S. Thousand, R. A. Villa, & A. I. Nevin (Eds.), *Creativity and collaborative learning: A practical guide to empowering students and teachers* (pp. 31–44). Baltimore: Paul H. Brookes.

Johnson, D. W., & Johnson, R. T. (2005). New developments in social interdependence theory. *Psychology Monographs, 131*(4), 285–358. doi: 10.3200/MONO.131.4.285-358

Johnson, D. W., & Johnson, R. T. (2009). An educational psychology success story: Social interdependence theory and cooperative learning. *Educational Researcher, 38*(5), 365–379. doi: 10.3102/0013189X09339057

Johnson, D. W., Johnson, R. T., & Smith, K. (1998). Cooperative learning returns to college: What evidence is there that it works? *Change: The Magazine of Higher Learning, 30*(4), 26–35. doi: 10.1080/00091389809602629

Johnson, D. W., Johnson, R. T., & Smith, K. (2007). The state of cooperative learning in postsecondary and professional settings. *Educational Psychology Review, 19*(1), 15–29. doi: 10.1007/s10648-006-9038-8

Jones, A., Küster, D., Basedow, C. A., Alves-Oliveira, P., Serholt, S., Hastie, H., … Castellano, G. (2015). Empathic robotic tutors for personalised learning: A multidisciplinary approach. In A. Tapus, E. André, J. C. Martin, F. Ferland, & M. Ammi (Eds.), *Lecture Notes in Computer Science: Vol. 9388. Social Robotics* (pp. 285–295). Berlin/ Heidelberg: Springer. doi: 10.1007/978-3-319-25554-5_29

Kelley, J. F. (1984). An iterative design methodology for user-friendly natural language office information applications. *ACM Transactions on Information Systems, 2*(1), 26–41. doi: 10.1145/357417.357420

Kelley, H. H., Kerr, N. L., Reis, H. T., Holmes, J. W., Rusbult, C. E., & van Lange, P. A. M. (2003). *An Atlas of Interpersonal Situations.* Cambridge: Cambridge University Press.

Khan S., & Germak, C. (2018). Reframing HRI design opportunities for social robots: Lessons learnt from a service robotics case study approach using UX for HRI. *Future Internet, 10*(10), 1–22. doi: 10.3390/fi10100101

Kim, Y., & Mutlu, B. (2014). How social distance might shape human-robot collaboration. *International Journal of Human-Computer Studies, 72*(12), 783–795. doi: 10.1016/j.ijhcs.2014.05.005

Kock, N. (2004). The psychobiological model: Towards a new theory of computer-mediated communication based on Darwinian evolution. *Organization Science, 15*(3), 327–348. doi:10.1287/orsc.1040.0071

Kock, N., & Hantula, D. A. (2005). Do we have e-collaboration genes? *International Journal of e-Collaboration, 1*(2), i–ix.

Komarraju, M., Karau, S. J., Schmeck, R. R., & Avdic, A. (2011). The Big Five personality traits, learning styles, and academic achievement. *Personality and Individual Differences, 51*(4), 472–477. doi: 10.1016/j.paid.2011.04.019

Kuo, H., Rabindran, J. M., Broadbent, E., Lee, Y. I., Kerse, N., Stafford, R. M. Q., & MacDonald, B. A. (2009). Age and gender factors in user acceptance of healthcare robots. *Proceedings of the 18th International Symposium on Robot and Human Interactive Communication* (RO-MAN 2009, Toyama, Japan), 214–219. doi: 10.1109/ROMAN.2009.5326292

Kyndt, E., Raes, E., Lismont, B., Timmers, F., Cascallar, E., & Dochy, F. (2013). A meta-analysis of the effects of face-to-face cooperative learning. Do recent studies falsify or verify earlier findings? *Educational Research Review, 10*, 133–149. doi: 10.1016/j.edurev.2013.02.002

Lee, E., Lee, Y., Kye, B., & Ko, B. (2008). Elementary and middle school teachers', students' and parents' perception of robot-aided education in Korea. *Proceedings of the World Conference on Educational Multimedia, Hypermedia and Telecommunications* (ED-Media 2008, Vienna, Austria), 175–183.

Leite, I., Castellano, G., Pereira, A., Martinho, C., & Paiva, A. (2014). Empathic robots for long-term interaction. Evaluating social presence, engagement and perceived support in

children. *International Journal of Social Robotics, 6*(3), 329–341. doi: 10.1007/s12369-014-0227-1

Lemaignan, S., Jacq, A., Hood, D., Garcia, F., Paiva, A., & Dillenbourg, P. (2016). Learning by teaching a robot: The case of handwriting. *IEEE Robotics & Automation Magazine, 23*(2), 56–66. doi: 10.1109/MRA.2016.2546700

Lin, Y. C., Liu, T. C., Chang, M., & Yeh, S. P. (2009). Exploring children's perceptions of the robots. In M. Chang, R. Kuo Kinshuk, C. D. Chen, & M. Hirose (Eds.), *Lecture Notes in Computer Science: Vol. 5670. Edutainment* (pp. 512–517). Berlin, Heidelberg: Springer. doi: 10.1007/978-3-642-03364-3_63

Liu, E. Z. F. (2010). Early adolescents' perceptions of educational robots and learning of robotics. *British Journal of Educational Technology, 41*(3), E44–E47. doi: 10.1111/j.1467-8535.2009.00944.x}

Lorenz, R., Endberg, M., & Eickelmann, B. (2016). Unterrichtliche Nutzung digitaler Medien von Lehrkräften der Sekundarstufe I in Deutschland und im Bundesländervergleich [Secondary school teachers' use of digital media in Germany]. In W. Bos, R. Lorenz, M. Endberg, B. Eickelmann, R. Kammerl, & S. Welling (Eds.), *Schule digital—der Länderindikator 2016* [*Digital school—country indicators*] (pp. 80–109). Münster/ New York: Waxmann.

Lubold, N., Walker, E., Pon-Barry, H., & Ogan, A. (2018). Automated pitch convergence improves learning in a social, teachable robot for middle school mathematics. *Proceedings of the 19th International Conference on Artificial Intelligence in Education* (AIED 2018, London, UK), 282–296. doi: 10.1007/978-3-319-93843-1_21

Marsh, J. C. (2004). Theory-driven versus theory-free research in empirical social work practice. In H. E. Briggs & T. L. Rzepnicki (Eds.), *Using evidence in social work practice: Behavioral perspectives* (pp. 20–35). Chicago, US: Lyceum Books.

Merdan, M., Lepuschitz, W., Koppensteiner, G., & Balogh, R. (2017). *Robotics in education. Research and practices for robotics in STEM education.* Berlin/ Heidelberg: Springer. doi: 10.1007/978-3-319-42975-5

Miller, D. P., Nourbakhsh, I. R., & Siegwart, R. (2008). Robots for education. In B. Siciliano & O. Khatib (Eds.), *Springer Handbook of Robotics* (pp. 1283–1301). Berlin/ Heidelberg: Springer. doi: 10.1007/978-3-540-30301-5

Moreno, R., Mayer, R. E., Spires, H. A., & Lester, J. C. (2001). The case for social agency in computer-based teaching: Do students learn more deeply when they interact with animated pedagogical agents? *Cognition and Instruction, 19*(2), 177–213. doi: 10.1207/S1532690XCI1902_02

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

Nass, C., Fogg, B. J., & Moon, Y. (1996). Can computers be teammates? *International Journal on Human-Computer Studies, 45*(6), 669–678. doi: 10.1006/ijhc.1996.0073

Nomura, T., Kanda, T., & Suzuki, T. (2006). Experimental investigation into influence of negative attitudes toward robots on human–robot interaction. *AI & Society, 20*(2), 138–150. doi: 10.1007/s00146-005-0012-7

Norton, M. I., Mochon, D., & Ariely, D. (2012). The IKEA effect. When labor leads to love. *Journal of Consumer Psychology, 22*(3), 453–460. doi: 10.1016/j.jcps.2011.08.002

Obaid, M., Barendregt, W., Alves-Oliveira, P., Paiva, A., & Fjeld, M. (2015). Designing robotic teaching assistants: Interaction design students' and children's views. In A. Tapus, E. André, J. C. Martin, F. Ferland, & M. Ammi (Eds.), *Lecture Notes in Computer Science: Vol. 9388. Social Robotics* (pp. 502–511). Berlin/ Heidelberg: Springer. doi: 10.1007/978-3-319-25554-5_50

Obaid, M., Yantaç, A. E., Barendregt, W., Kırlangıç, G., & Göksun, T. (2016). Robo2Box: A toolkit to elicit children's design requirements for classroom robots. In A. Agah, J.-J. Cabibihan, A. M. Howard, M. A. Salichs, & H. He (Eds.), *Lecture Notes in Artificial Intelligence: Vol. 9979. Social Robotics* (pp. 600–610). Berlin/ Heidelberg: Springer. doi: 10.1007/978-3-319-47437-3_59

Oros, M., Nikolić, M., Borovac, B., & Jerković, I. (2014). Children's preference of appearance and parents' attitudes towards assistive robots. *Proceedings of the 14th International Conference on Humanoid Robots* (HUMANOIDS 2014, Madrid, Spain), 18–20. doi: 10.1109/HUMANOIDS.2014.7041385

Paulovich, B. (2015). Design to improve the health education experience: Using participatory design methods in hospitals with clinicians and patients. *Visible Language, 49*(1-2), 108–123.

Plauska, I., & Damaševičius, R. (2014). Educational robots for internet-of-things supported collaborative learning. *Proceedings of the International Conference on Information and Software Technologies* (ICIST 2014, Druskininkai, Lithuania), 346–358. doi: 10.1007/978-3-319-11958-8_28

Randall, T., Terwiesch, C., & Ulrich, K. T. (2007). User design of customized products. *Marketing Science, 26*(2), 268–280. doi: 10.1287/mksc.1050.0116

Reich, N., & Eyssel, F. (2013) Attitudes towards service robots in domestic environments. The role of personality characteristics, individual interests, and demographic variables. *Journal of Behavioral Robotics, 4*(2), 123–130. doi: 10.2478/pjbr-2013-0014

Reich-Stiebert, N., & Eyssel, F. (2017). (Ir)relevance of gender? On the influence of gender stereotypes on learning with a robot. *Proceedings of the 12th International Conference on Human-Robot Interaction* (HRI 2017, Vienna, Austria), 166–176. doi: 10.1145/2909824.3020242

Reeves, B., & Nass, C. (1996). *The media equation: How people treat computers, television, and new media like real people and places*. Chicago: The Center for the Study of Language and Information Publications.

Riek, L. D., & Howard, D. A. (2014). A code of ethics for the human-robot interaction profession. *Proceedings of the Inaugural Conference on Legal and Policy Issues Relating to Robotics* (We Robot 2014, Coral Gables, Florida), 1–10.

Šabanović, S. (2010). Robots in society, society in robots. Mutual shaping of society and technology as a framework for social robot design. *International Journal of Social Robotics, 2*(4), 439–450. doi: 10.1007/s12369-010-0066-7

Saerbeck, M., Schut, T., Bartneck, C., & Janse, M. D. (2010). Expressive robots in education: Varying the degree of social supportive behavior of a robotic tutor. *Proceedings of the Conference on Human Factors in Computing Systems* (CHI 2012, Atlanta, USA), 1613–1622. doi: 10.1145/1753326.1753567

Schneider, S., Riether, N., Berger, I., & Kummert, F. (2014). How socially assistive robots supporting on cognitive tasks perform. *Proceedings of the 50th Anniversary Convention on Artificial Intelligence and Simulation for Behaviour* (AISB 2014, London, UK), 1–6.

Schulz, T., & Herstad, J. (2017). Walking away from the robot: Negotiating privacy with a robot. *Proceedings of the 31st International BCS Human Computer Interaction Conference* (HCI 2017, Sunderland, UK), 1–6. doi: 10.14236/ewic/HCI2017.83

Selwyn, N. (2007). The use of computer technology in university teaching and learning: A critical perspective. *Journal of Computer Assisted Learning, 23*(2), 83–94. doi: 10.1111/j.1365-2729.2006.00204.x

Serholt, S., & Barendregt, W. (2014). Students' attitudes towards ethical dilemmas in the possible future of social robots in education. *Proceedings of the 23rd International*

Symposium on Robot and Human Interactive Communication (RO-MAN 2014, Edinburgh, Scotland), 955–960.

Serholt, S., Barendregt, W., Leite, I., Hastie, H., Jones, A., Paiva, A., Vasalou, A., & Castellano, G. (2014). Teachers' views on the use of empathic robotic tutors in the classroom. *Proceedings of the 23rd International Symposium on Robot and Human Interactive Communication* (RO-MAN 2014, Edinburgh, Scotland), 955–960. doi: 10.1109/ROMAN.2014.6926376

Shin, N., & Kim, S. (2007). Learning about, from, and with robots: Students' perspectives. *Proceedings of the 16th International Conference on Robot and Human Interactive Communication* (RO-MAN 2007, Jeju, South Korea), 1040–1045. doi: 10.1109/ROMAN.2007.4415235

Slavin, R. E. (1996). Research on cooperative learning and achievement: What we know, what we need to know. *Contemporary Educational Psychology, 21*(1), 43–69. doi: 10.1006/ceps.1996.0004

Sless, D. (2008). Measuring information design. *Information Design Journal, 16*(3), 250–258. doi: 10.1075/idj.16.3.11sle

SoftBank Robotics. NAO. Solutions for education & research. Retrieved from https://www.aldebaran.com/en/solutions/education-research.

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. doi: 10.5898/JHRI.1.1.Tanaka

Teo, T. (2006). Attitudes toward computers: A study of post-secondary students in Singapore. *Interactive Learning Environments, 14*(1), 17–24. doi: 10.1080/10494820600616406

Tesser, A., & Conlee, M. C. (1975). Some effects of time and thought on attitude polarization. *Journal of Personality and Social Psychology, 31*(2), 262–270. doi: 10.1037/h0076292

The LEGO Group. LEGO MINDSTORMS. Retrieved from https://www.lego.com/en-us/mindstorms/build-a-robot

Thompson, B. (2008). How college freshman communicate student academic support: A grounded theory study. *Communication Education, 57*(1), 123–144. doi: 10.1080/03634520701576147

Thompson, B., & Mazer, J. P. (2009a). Student academic support: A validity test. *Communication Research Reports, 28*(3), 214–224. doi: 10.1080/08824096.2011.586074

Thompson, B., & Mazer, J. P. (2009b). College student ratings of student academic support: Frequency, importance, and modes of communication. *Communication Education, 58*(3), 433–458. doi: 10.1080/03634520902930440

Tinto, V. (1997). Classrooms as communities: Exploring the educational character of student persistence. *Journal of Higher Education, 68*(6), 599–623. doi: 10.2307/2959965

Tsiakas, K., Abujelala, M., & Makedon, F. (2018). Task engagement as personalization feedback for socially-assistive robots and cognitive training. *Technologies, 6*(2), 1–17. doi: 10.3390/technologies6020049

Ushida, H. (2010). Effect of social robot's behavior in collaborative learning. *Proceedings of the 5th International Conference on Human-Robot Interaction* (HRI 2010, Osaka, Japan), 195–196. doi: 10.1109/HRI.2010.5453199

Verešová, M. (2015). Learning strategy, personality traits and academic achievement of university students. *Social and Behavioral Sciences, 147*, 3473–3478. doi: 10.1016/j.sbspro.2015.01.1021

Vink, P., Imada, A. S., & Zink, K. J. (2008). Defining stakeholder involvement in participatory design processes. *Applied Ergonomics, 39*(4), 519–536. doi: 10.1016/j.apergo.2008.02.009

Walters, M. L., Koay, K. L., Syrdal, D. S., Dautenhahn, K., & Te Boekhorst, R. (2009). Preferences and perceptions of robot appearance and embodiment in human-robot interaction trials. *Proceedings of the New Frontiers in Human-Robot Interaction Symposium* (AISB 2009, Edinburgh, Scotland), 136–143.

Walters, M. L., Syrdal, D. S., Dautenhahn, K., Te Boekhorst, R., & Koay, K. L. (2008). Avoiding the uncanny valley: Robot appearance, personality and consistency of behavior in an attention-seeking home scenario for a robot companion. *Autonomous Robots, 24*(2), 159–178. doi: 10.1007/s10514-007-9058-3

Woods, S., Dautenhahn, K., & Schulz, J. (2004). The design space of robots: Investigating children's views. *Proceedings of the 13th International Workshop on Robot and Human Interactive Communication* (RO-MAN 2004, Kurashiki, Japan), 47–52. doi: 10.1109/ROMAN.2004.1374728

Yager, S., Johnson, R. T., Johnson, D. W., & Snider, B. (1986). The impact of group processing on achievement in cooperative learning groups. *The Journal of Social Psychology, 126*(3), 389–397. doi: 10.1080/00224545.1986.9713601

Zajonc, R. B. (1986). The attitudinal effects of mere exposure. *Journal of Personality and Social Psychology, 92*(2), 1–27. doi: 10.1037/h0025848

Złotowski, J., Sumioka, H., Nishio, S., Glas, D. F., Bartneck, C., & Ishiguro, H. (2016). Appearance of a robot affects the impact of its behaviour on perceived trustworthiness and empathy. *Journal of Behavioral Robotics, 7*(1), 55–66. doi: 10.1515/pjbr-2016-0005

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Reich-Stiebert, N., Eyssel, F., & Hohnemann, C. (2019). Involve the user! Changing attitudes toward robots by user participation in a robot prototyping process. *Computers in Human Behavior, 91*, 290–296. doi: 10.1016/j.chb.2018.09.041

Reich-Stiebert, N., & Eyssel, F. (2018). Investigating the practicability and effectiveness of cooperative learning in human-robot interaction. Unpublished manuscript.

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DECLARATION OF MANUSCRIPT AUTHORSHIP

Frau Natalia Reich-Stiebert war hauptverantwortlich für die Versuchsplanung, Durchführung und Datenauswertung der empirischen Studien. Sie verfasste und überarbeitete alle Manuskripte selbstständig. Die gesamte empirische Arbeit und die Verfassung der Manuskripte entstand unter Betreuung von und in Ko-Autorenschaft mit Frau Prof. Dr. Friederike Eyssel. Des Weiteren wirkte die Studentin Frau Charlotte Hohnemann an zwei Studien und den entsprechenden Manuskripten als Ko-Autorin mit.

_____   _____   _____

(Prof. Dr. F. Eyssel)   (Charlotte Hohnemann)   (Natalia Reich-Stiebert)

STATEMENT OF ORIGINALITY

Ich versichere, dass ich meine Dissertation "Acceptance and Applicability of Educational Robots: Evaluating Factors Contributing to a Successful Introduction of Social Robots into Education" selbstständig und ohne die Hilfe Dritter angefertigt habe. Alle Textstellen, die wörtlich oder sinngemäß anderen Quellen entstammen, habe ich als solche kenntlich gemacht. Die Dissertation wurde in der gegenwärtigen oder einer ähnlichen Fassung bei keiner anderen Hochschule eingereicht und hat keinem Prüfungszweck gedient.

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(Ort, Datum)   (Natalia Reich-Stiebert)

APPENDIX

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APPENDIX

Investigating the Practicability and Effectiveness of Cooperative Learning

in Human-Robot Interaction

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Abstract

The present work adopted a multidisciplinary and theory-driven approach to tackle the practicability of implementing cooperative learning principles in human-robot interaction (HRI), and investigated their effectiveness on learning performance, affective state, and the evaluation of the robot as a learning companion. In particular, we focused on positive interdependence, direct face-to-face interaction, social support, and feedback regarding the learning process. Our findings predominantly underpinned the practicability of cooperative learning in HRI: First, a physical robot as opposed to its virtual counterpart emanated greater social presence in a learning interaction. Second, participants perceived the allegedly supportive robot to provide more social support than the neutral robot. Third, students positively evaluated the feedback session with the robot.

Concerning the effectiveness of cooperative learning in HRI, however, we only obtained significant findings regarding direct face-to-face interaction: Respondents found the physically embodied robot more intrinsically motivating, deemed it warmer and more competent, and ascribed it higher educational capabilities than the virtual robot. Although the other principles of cooperative learning did not produce the anticipated effects, we suggest that future work should adopt this well-established approach into HRI as numerous findings from educational psychological research indicate its tremendous potential. It remains to be clarified in prospective research, though, how this potential can be effectively realized in HRI.

Keywords: cooperative learning, human-robot interaction, educational robots, interdependence theory, embodiment, feedback

Introduction

Digital technologies have a profound impact on the educational landscape and considerably shape educational practices at different levels. Currently, technologies such as interactive whiteboards or one–to–one tablet computers are no longer surprising innovations in today's classrooms. Robots, however, as the latest form of digital media in education, offer new potential for shaping teaching and learning. Indeed, it is the case that the use of social robots as tools for supporting teaching and learning has become increasingly important at different educational levels, reaching from elementary to graduate programs (Alimisis, 2013; Šabanović, Berry, & Bethel, 2017). In this matter, the role of robots in education is twofold: First, robots can serve as tools to teach science, technology, engineering and mathematics (STEM). Robots can be used as objects to learn programming or as instruments to discover how to build robots as an end in itself (Miller & Nourbakhsh, 2016). Second, robots as pedagogical means can serve as social interaction partners that support students' learning (Belpaeme, Kennedy, Ramachandran, Scassellati, & Tanaka, 2018; Miller, Nourbakhsh, & Siegwart, 2008).

In the present research, we will concentrate on the latter role of educational robots and discuss their application potential from a social and educational psychological viewpoint. With regard to the application of educational robots as learning collaborators, research has clearly indicated the positive effects of learning with robots on cognitive and affective outcomes (see Belpaeme et al. (2018) for a review). In a range of works it has been found that educational robots contribute to higher learning gains and knowledge acquisition (e.g., Leyzberg, Spaulding, Toneva, & Scassellati, 2012; Saerbeck, Schut, Bartneck, & Janse, 2010; Szafir & Mutlu, 2012). Likewise, it has been shown that learning with educational robots positively affects students' motivation and engagement (e.g., Köse et al., 2015; Saerbeck et al., 2010), collaboration among

students (Mitnik, Nussbaum, & Soto, 2008), and compliance with the learning instructions (e.g., Bainbridge, Hart, Kim, & Scassellati, 2011; Ramachandran, Huang, Gartland, & Scassellati, 2018).

Despite the numerous studies indicating the beneficial effects of implementing robots into education (see Belpaeme et al., 2018; Benitti, 2013), far too little attention has been paid to investigating well-established pedagogical methods and concepts when it comes to facilitating learning with robots. Not infrequently, attempts to apply robots for learning "underestimate the role of pedagogy that should support any such attempt" (Alimisis, 2012, p. 7). However, it is precisely the recourse to educational methodologies and the creation of sophisticated supportive learning environments that will lead "any educational innovation, including robotics, to success" (Alimisis, 2012, p. 7). A widely discussed educational approach that strengthens the application of robots in learning environments (e.g., Catlin & Blamires, 2010; Denis & Hubert, 2001; Yousuf, 2009) is traced back to the theory of constructivism by Piaget (1954). Based on Piaget's assumptions about learning as an active, constructive process, Papert (1980) developed the theory of constructionism. According to Papert's theory, students learn when they actively construct physical objects, for instance, when they build and program physical robots (Papert, 1980). These theoretical assumptions apply to the first role of robots in education, namely, using the robot as a tool for programming and building. Regarding the second role of robots in education, more specifically, the use of educational robots as collaborators to support learning, only few studies draw on pedagogical theories and methods. To date, some studies have already investigated the learning by teaching paradigm in the context of human-robot learning (Lemaignan et al., 2016; Tanaka & Matsuzoe, 2012; Werfel, 2013) stressing its good applicability and effectiveness with respect to learning performance and engagement. By

investigating the effect of social supportive behavior expressed by an educational robot, Saerbeck and colleagues (2010) referred back to theoretical assumptions by Tiberius and Billson (1993) who concentrated on social contexts of learning. For implementing social supportive behavior, Saerbeck and colleagues extracted aspects of social supportive behavior displayed by teachers in student-teacher relationships. Findings indicated that the application of social supportive behavior increased students' learning performance. Szafir and Mulu (2012) relied on the concept of immediacy from educational psychology that constitutes "the degree of perceived physical or psychological closeness between people" (Szafir & Mutlu, 2012, p. 12). Szafir and Mutlu implemented verbal (e.g., inclusive and mutual communication style) and non-verbal (e.g., proximity, facial expressions) immediacy cues that were identified in student-teacher interaction in learning interactions with a robot. The results revealed that learning with an educational robot that displayed high immediacy resulted in higher learning outcomes (regardless of participant gender) and higher motivation among female participants.

Nonetheless, these attempts to integrate educational methods into human-robot learning interactions are far from making comprehensive use of the potential of different established pedagogical approaches. Since, however, the recourse to educational methodologies can lead the use of educational robots to success, it seems crucial to elaborate further meaningful pedagogical concepts that will help to guide and facilitate human-robot interaction (HRI) in learning settings. The present research generates insights into this issue by taking a theory-driven perspective and implementing key principles of cooperative learning (CL)—a well-known and well-researched teaching approach in education—in human-robot learning.

Cooperative Learning

CL is one of the most successful instructional practices in education, it can be utilized in every domain area and for students of all ages reaching from preschool to academic institutions (see Johnson & Johnson, 2009; Johnson, Johnson, & Smith, 2007; Slavin, 1992, 1996). CL has its origins in social interdependence theory that emerged from social and educational psychology (Johnson & Johnson, 2009). Initially designated "The theory of Co-operation and Competition" (Deutsch, 1949), social interdependence theory was developed to describe cooperation and competition in the functioning of small groups (Deutsch, 1949). It does not exist a recognized definition of CL, however, it is described as an approach in which students learn together to accomplish shared goals (Johnson & Johnson, 1999). CL comprises various teaching methods in which students work in small groups to promote each other's learning (Slavin, 1996). Based on Deutsch's assumptions on social interdependence (1949), Johnson and Johnson posited that CL would encompass five essential components (Johnson & Johnson, 1989, 2009; Johnson, Johnson, & Smith, 1991). These are: social interdependence, individual accountability, direct face-to-face interaction, appropriate use of social skills, and group processing (Johnson & Johnson, 1989, 2009; Johnson et al., 1991).

Social interdependence implies that the success of one learner is dependent on the success of the other learners. According to this, group members have to understand that each individual's effort benefits not only the individual itself, but all group members as well. To achieve this, group members have to work together and to coordinate their actions (Johnson & Johnson, 1992, 2009). Positive interdependence creates feelings of individual accountability to complete one's part of the work and to contribute to the group work. Learners have to internalize that although they learn together, they have to perform alone and that each learner has to exert

the same effort in achieving the group goal (Johnson & Johnson, 2005, 2009). As individual accountability results from positive interdependence, they are strongly interlinked (Johnson & Johnson, 2009). Therefore, we excluded this factor from the scope of our investigation as it comes along with positive interdependence. Face-to-face interaction involves physical proximity that is required to ensure that learners can interact directly when they learn together. Direct contact promotes, for instance, assistance to group mates, problem-solving, exchanging resources, or providing feedback (Johnson & Johnson, 2009). Effective cooperation requires an appropriate use of social skills. Students have to communicate unambiguously, support each other, and resolve conflicts constructively (Johnson, 2009; Johnson & Johnson, 2009). Socially competent students not only show higher learning achievements, but also build more positive relationships to other group members (Johnson & Johnson, 2009; Putnam, Rynders, Johnson, & Johnson, 1989). Group processing comprises the reflection of the learning process, mutual feedback on helpful and unhelpful actions, and the decision which activities should be changed or maintained for future learning (Johnson & Johnson, 2009). In doing so, group goals become clearer and the effectiveness of CL will improve (Weldon & Weingart, 1993).

Research Questions

Psychologists and educators increasingly call for applying interdisciplinary approaches and theory-driven perspectives when tackling questions related to the usage of social robots (e.g., Alimisis, 2012; Eyssel, 2016). Even more important, the recourse to educational methodologies in HRI can contribute to the creation of supportive learning environments with robots (Alimisis, 2012), especially in light of the fact that educational robotics lacks of systematic investigations and reliable experimental designs (see Alimisis, 2013). To counter these issues, the purpose of

the present studies was to examine the effectiveness of implementing elements of CL in dyadic

HRI learning. First, we explored whether, and as the case may be, how inducing social

interdependence (vs. social independence) affects learning. We were interested in whether an

interdependently perceived learning relationship would affect students' learning outcomes,

affective state, and their evaluation of the robot (research question 1). Second, we wanted to

investigate the effect of direct face-to-face interaction with a robot on the learning interaction.

More specifically, we sought to clarify the impact of learning with a physically present (vs.

virtually present) robot on students' learning performance and the interaction (research question

2). Third, we focused on the effectiveness of implementing social skills in a robots' behavior on

HRI. Particularly, we attempted to examine how socially supportive behavior (vs. neutral

behavior) provided by a robot during HRI affects students' learning and the learning interaction

(research question 3). Fourth, we wanted to scrutinize the effects of group processing with a

robot on future learning. That is, we investigated whether giving and receiving feedback

regarding the learning process (vs. no feedback on the learning process) affects students' future

learning and their perception of the robot as a learning companion (research question 4).

General Method

Sample and design

In each of our four experiments, we implemented a single factor between-subjects design

with two factor levels resulting in two conditions. To determine the sample size a priori, we

conducted a power analysis with G*Power (Faul, Erdfelder, Lang, & Buchner, 2007) using the

following parameters: $\alpha = .05$; power $= .80$; $f^2 = 0.25$ (medium effect). The result suggested to

include at least 33 participants in each condition. Participants were university students from

different departments who were recruited at Bielefeld University.

Experimental setup

In each experiment, participants were tested individually in a laboratory at the university.

Before the HRI started, the experimenter informed participants that they will learn a new Robot

Interaction Language (ROILA) with the robot NAO (SoftBank Robotics) and that NAO would

interact autonomously and explain the learning interaction. Afterwards the experimenter left the

room. To confirm the impression that the robot acts autonomously, we used the Wizard-of-Oz

technique (Kelley, 1984) that allows the experimenter to remotely control the robot from another

lab and to operate the robot in synchrony with participants' individual learning pace. Following

the learning interaction, the robot asked participants to complete a computerized questionnaire

using a laptop that was placed on another table in the laboratory. The questionnaire included the

dependent measures and demographic information. Finally, participants were debriefed,

reimbursed (three euros and chocolate, or course credit), and dismissed.

Robot behavior

In each experiment, the robot was always introduced as learning companion that would

learn with the participant ROILA. In doing so, we avoided to create the notion of the robot as a

teacher or instructor and the student as passive learner as such teacher-centered approaches

represent conventional instructional methods which have become obsolete in today's teaching

practice (e.g., Johnson & Johnson, 2009; Lea, Stephenson, & Troy, 2003). During the learning

interaction the robot used speech, humanlike gaze, and deictic gestures to impart the learning

contents. Based on previous findings that indicate that applying humanlike gaze in HRI leads to

improved collaborative work and a positive perception of the robot, and that the use of deictic

gestures supports information recall (Huang & Mutlu, 2012, 2013, 2014; Salem, Kopp, Wachsmuth, Rohlfing, & Joublin, 2012), the robot in our studies showed behavior synchronized with regard to speech, gaze, and gestures. For instance, it always looked at the participants while talking and gazed toward the learning folder (see section on *Materials*) synchronously performing deictic gestures accompanied by speech to indicate participants to use the learning folder. To refer to correct or wrong answers, the robot supported its verbal feedback by nodding or shaking its head. During individual learning phases the robot looked around the room slightly moving its head. Throughout the whole interaction the robot remained seated at the table and displayed, apart from the described gestures, no other behaviors in order not to distract participants from the learning interaction as such occurrence was observed in previous work (Huang & Mutlu, 2013).

Materials

In all experiments, participants had to learn basic vocabulary and simple grammar lessons of the artificial Robot Interaction Language (ROILA). ROILA is a spoken language for communicating with robots (Mubin et al., 2012; Mubin, Henderson, & Bartneck, 2013). This language is easy to learn for humans and optimized for the robot's speech recognition. Due to several reasons, we chose this language for our learning scenario: First, given the novelty of ROILA, it ensured better comparability of participants' learning outcomes as participants should not have prior knowledge of the learning contents. However, we always asked for participants' existing ROILA skills to control for prior knowledge. Second, ROILA is based on natural languages and has a simple grammar making it very easy to learn. This guarantees learning of several words and smaller sentences even in very short learning interactions. Third, as ROILA is an artificial language constructed for interaction with robots, it increases the credibility of our

cover story. Namely, we wanted students help to extend NAO's ROILA knowledge and further test how quickly humans can learn ROILA.

For this purpose, we provided participants with a learning folder on ROILA learning materials including a table of all letters used in ROILA (a, e, i, o, u, b, f, j, k, l, m, n, p, s, t, w), sample words to practice the pronunciation (e.g., jinolu, saki, losa), a short vocabulary list, and example sentences to practice the sentence structure (e.g., "I am a robot." – "Pito lobo."). All learning contents were explained by the robot and were only sparsely presented in the folder (e.g., only the letters and a few words and no additional information were presented). This was done in order to warrant that participants paid greater attention to the NAO robot and its detailed explanations on ROILA. In our studies, we used the robot as central learning tool and provided learners only with short written learning materials. We avoided to use laptops or touchscreens as prior work using these hardware configurations has shown that participants tend to gaze more toward a screen than the robot (see Baxter et al., 2013). In addition to the folder, participants received an index card with new ROILA vocabulary. The robot was assumingly unfamiliar with these words, and participants were required to teach the robot by sharing their knowledge on the new words.

Instruments and measures

After the learning interaction, the robot asked participants to fill in a questionnaire to help continue its development as an educational robot. Participants could rate their agreement of each construct on a 7-point Likert scale ranging from 1 (*fully disagree*) to 7 (*fully agree*). Items were recoded where necessary with higher values indicating stronger endorsement of the respective construct.

Learning performance. Participants were first tested on their ROILA knowledge. To do so, participants had to translate six German words and three short sentences into ROILA (i.e., "The girl is small.").

Affective state. To evaluate participants' affective state during the learning interaction, we assessed intrinsic motivation, self-efficacy for learning and performance, and learning mood. We used the German short version of the *Intrinsic Motivation Inventory* proposed by Wilde, Bätz, Kovaleva, and Urhahne (2009; original version: Deci & Ryan, 2003) that included nine items (e.g., "I enjoyed learning with NAO"). Second, to examine participants' self-efficacy for learning and performance, we assessed a subscale from the *Motivated Strategies for Learning Questionnaire* (Pintrich, Smith, Garcia, & McKeachie, 1993) and amended it slightly to our learning context. An example item read: "I'm confident that I learned the basic ROILA vocabulary". Third, we measured participants' learning mood by applying a short version of an instrument developed by Krämer, Simons, and Kopp (2007). Participants had to rate their feelings during the learning interaction with the robot on ten items (e.g., attentive, relaxed).

Evaluation of the robot. To examine participants' perception of the robots' usefulness as learning companion, we adapted and amplified the *Perceived Usefulness and Ease of Use Scales* (Davis, 1989) to the context of human-robot learning. The resulting scale included 15 items (e.g., "NAO improved my learning performance") that evaluated participants' satisfaction with the robot as learning companion. Further, to explore participants' impression of the robots' educational qualities, we used a short version of the *Agent Persona Instrument* (Baylor & Ryu, 2003; German translation by Krämer, 2008). The scale included 15 items that measured how engaging the robot was, its credibility, and human-likeness (e.g., "NAO was knowledgeable"). Finally, we measured participants' impression of the robots' warmth and competence by using an

adapted and shortened version of a scale developed by Fiske, Cuddy, Glick, and Xu (2002). Participants had to rate their impression of the robot on a 12-item scale (e.g., "comprehensible", "likeable").

Control variables. Previous research in the field of robotics has shown that technical affinity and prior robot experience significantly affect the evaluation and acceptance of robots (e.g., Arras & Cerqui, 2005; Bartneck, Suzuki, Kanda, & Nomura, 2006; Reich & Eyssel, 2013; Reich-Stiebert & Eyssel, 2015). In order to control for these variables, we measured participants' technical affinity by using a short version of the *Technology Commitment* scale (Neyer, Felber, & Gebhardt, 2012). The scale consisted of eight items (i.e., "I am very curious about new technical developments"). To assess prior robot experience, we asked participants to indicate whether they already participated in a study with the NAO robot or another robot, (dummy coded: 1 = *yes*, 2 = *no*). Further, to control for participants' previous knowledge of the learning content, we asked participants whether they already knew the ROILA language (dummy coded: 1 = *yes*, 2 = *no*).

Study 1 – Social Interdependence in Human-Robot Learning

The first principle of cooperative learning is social interdependence between learners. To our knowledge, social interdependence theory has hardly been considered in HRI research so far. Some studies have concentrated on interdependence theory to analyze interactions in joint activities between humans and robots (e.g., Johnson, Bradshaw, Feltovich, Hoffman, et al., 2011; Johnson, Bradshaw, Feltovich, Jonker, et al., 2014; Wagner & Arkin, 2006). However, although in these studies the robot was considered as a teammate in different interaction scenarios, the interactions were less social in their nature as they concentrated on fulfilling tasks in work

systems or in the field (e.g., mitigate natural disasters, cleanup a toxic waste spill, etc.). The application of social interdependence theory to social HRI in a stricter sense (e.g., social interactions in home, care, or learning contexts), has not been explored satisfactorily to our knowledge. Only a few works have marginally taken into account the concept of interdependence in social HRI: By investigating the evaluation of social presence in robots over longer periods of time, Leite, Martinho, Pereira, and Paiva (2009) have explored affective and behavioral interdependence—subdimensions of social presence—among children and a robot. In a chess-playing scenario, children interacted with a robot and were afterwards asked to complete a questionnaire on social presence. Interestingly, the two dimensions affective interdependence (the extent to which a person's emotional and attitudinal state affects an interactant's emotional and attitudinal state and vice versa) and behavioral interdependence (the extent to which a person's behavior affects and is affected by an interactant's behavior) decreased during the experiment. The authors argue that the robot was perceived more like an independent chess interface than a companion over time. Kim and Mutlu (2014) have studied how social distance influences people's responses to robots. One aspect of their manipulation concerned interdependent vs. independent task goals. That is, in a cooperative task condition, participants were required to work interdependently with a robot to achieve a given goal, while in the competitive task condition participants had to achieve the goal independently of the robot. As before, however, results revealed no differences between the inter- and independent conditions. In consideration of these findings, much uncertainty still exists about the nature of interdependent interactions of humans and robots in social settings like learning interactions. Thus, the importance and originality of the present study is rooted in exploring the practicability

of inducing social interdependence between a human and an educational robot, and its impact on the learning interaction.

Hypotheses. In line with findings from educational research, we hypothesized that participants in the socially interdependent learning condition would have better learning outcomes (H1a), would report a more positive affective state (i.e., higher intrinsic motivation and self-efficacy, more positive learning mood; H1b), and would evaluate the robot more positively (i.e., higher educational impact, perceived usefulness, and more warmth and competence; H1c) compared to participants in the socially independent learning condition.

Method

Participants. Participants were $N = 68$ university students (42 female, 26 male) ranging in age from 17 to 46 years ($M = 24.46$, $SD = 5.90$). Apart from the above described reimbursement (see section on *General Method, Experimental Setup*), participants could further join in a raffle of an e-book. This additional reimbursement was due to the study design and will be explained in detail in the following section.

Experimental conditions. Social interdependence exists "when the outcomes of individuals are affected by their own and others' actions" (Johnson & Johnson, 2009, p. 366). In this case, a distinction is made between positive (learners' actions support the realization of common goals) and negative (learners' actions hinder the realization of common goals) interdependence (Deutsch, 1962; Johnson & Johnson, 1999, 2005, 2009). As our approach aimed at investigating factors influencing *successful* learning with robots, we only focused on implementing positive interdependence. We manipulated dependency in the learning interaction by referring back to resource, reward, and goal interdependence, which have been shown to induce positive interdependence (see Deutsch, 1962; Johnson & Johnson, 1994; Slavin, 1996).

Goal interdependence is achieved when learners are aware that they can achieve their goals only when the other learners achieve their own goals (Deutsch, 1962; Johnson & Johnson, 1989). With respect to the present study, goal interdependence was induced by telling participants that they—as well as the robot—have to know and answer questions on ROILA vocabulary after the learning interaction (Instruction by the experimenter: "You reach your common goal if both of you can answer questions on the newly learned ROILA vocabulary"). On the contrary, in the control condition participants were told that they have to answer questions on ROILA vocabulary after the learning interaction (Instruction by the experimenter: "The learning goal is reached if you can answer questions on the newly learned ROILA vocabulary").

Resource interdependence implies a complementary distribution of resources to the learners (Johnson & Johnson, 1989, 2009; Johnson et al., 2007). In our study, one part of the ROILA vocabulary was provided by the robot, while participants contributed another part of new ROILA vocabulary to the robot. By using an index card with new ROILA vocabulary (for details see section on *General Method, Materials*), participants were asked to pronounce and translate the vocabulary for the robot. In contrast, in the control condition participants were not taught by the robot and learned the new vocabulary independently by using the learning folder. Thus, participants and the robot were independent with respect to the learning resources.

Finally, reward interdependence is defined when the reward of an interaction partner depends on the performance of other group members (Wageman, 2001; Wageman & Baker, 1997). To manipulate reward interdependence, we told participants that they could join in a raffle of an e-book, while the reward for the robot would be its further development as an educational robot. In turn, in the control condition, participants were not informed about any reward for

successfully learning with the robot. However, for reasons of fairness, participants in the control condition could subscribe for joining in the raffle after finishing the experiment.

In addition to manipulating goal, resource, and reward interdependence, we made different use of the wording in the learning interactions between the two conditions to further stress an interdependent or independent learning interaction, respectively: In the experimental condition, the robot used pronouns and adjectives like "we", "together", "both of us", "mutual", etc. that emphasize a feeling of communality, while in the control condition the robot expressed pronouns like "you", "I/ me", etc. that illustrate a more individualistic character of the learning task.

Manipulation check. To check whether participants had perceived the learning interaction with the robot as independent or interdependent, we asked participants to indicate on a 7-point Likert scale (1 = *fully disagree*, 7 = *fully agree*) their impression of the learning interaction. Due to the lack of an adequate measure for social interdependence between robots and humans during learning interactions, we developed a 10-item scale that was partially derived from the *Perceived Behavioral Interdependence* subscale of the *Social Presence Measure* by Harms and Biocca (2004). An example items read: "NAO's behavior was in direct response to my behavior". Higher values reflect a higher endorsement of social interdependence with the robot, while lower values suggest a greater feeling of social independence with the robot.

Results

Preliminary analyses. First, we investigated descriptive statistics and internal consistencies (Cronbach's α) for all measures; the results are displayed in Table 1. With respect to reliabilities, all measures proved to be reliable to highly reliable (α = .83 – .94). Subsequently, to examine the relation between our measures, we conducted a bivariate correlation analysis

(Pearson's *r*) with our key study measures; the results are presented in Table 2. Our findings showed that all depended measures were moderately to highly intercorrelated (all *p*s < .05).

Manipulation check. Regarding the effectiveness of our manipulation, we conducted an independent samples *t*-test to compare participants' perceived interdependence with the robot during the learning interaction as a function of experimental condition (socially interdependent vs. socially independent learning). Surprisingly, no difference between the social interdependence (*M* = 5.08, *SD* = 1.13) and the social independence (*M* = 5.02, *SD* = 0.90) conditions were found, *t*(64) = 0.24, *p* = .81. In both conditions, participants perceived the learning interaction with the robot as rather interdependent.

Hypotheses testing. According to our apparently failed manipulation, a multivariate analysis of covariance (MANCOVA) to evaluate the impact of learning interaction (socially interdependent vs. socially independent learning) on learning outcomes (H1a), affective state (intrinsic motivation, self-efficacy, learning mood; H1b), and the evaluation of the robot (educational capabilities, perceived usefulness, warmth and competence; H1c) did not reveal any significant effect, *F* < 1. No significant differences emerged between the socially interdependent and socially independent learning conditions with respect to learning performance, affective state, and the evaluation of the robot.

Discussion

This is the first study to explore social interdependence in learning interactions between a human and a robot. Unexpectedly, our manipulation failed to induce positive interdependence (although positively pretested) between the robot and the participants, and congruently, we found no significant differences with respect to our dependent measures. Establishing an interdependent learning situation, however, exactly requires that students "[…] perceive that they

are positively interdependent with other members of their learning group […]" (Johnson et al., 2007, p. 23). The lack of expected results could be substantiated by assumptions on the *interdependence space* (Kelley, Kerr, Reis, Holmes, Rusbult, & van Lange, 2003). One dimension that defines the interdependence space is the *degree of interdependence* that captures the extent to which a person's outcomes are influenced by another person's actions. High interdependence exists in a situation in which an individual's outcomes highly depend on actions of another individual, whereas low interdependence occurs when an individual's actions are less dependent of another individual's actions. It can be assumed that, although we manipulated interdependence on three levels (viz., task, goal, and reward interdependence), in our learning interaction a rather low feeling of interdependence prevailed. This was probably due to the artificially created dependence situation and the consequent insignificance to achieve the given goal. In a more natural learning environment (e.g., a classroom), with real tasks and higher importance to successfully fulfil a task (e.g., to get a good mark in a test), interdependence with an educational companion robot probably could be perceived more clearly. Contrary to these assumptions, however, we have to point out that participants regarded the learning interactions as rather interdependent in both conditions. This discrepancy could be attributed to the difficulty of inducing an explicitly independent learning interaction without simultaneously imparting a competing atmosphere: Regarding resource interdependence, participants were independent of the robot to learn ROILA vocabulary, while the robot was dependent on the participants to learn the new vocabulary. With respect to reward interdependence, participants in the control condition also received a reward to a certain extent. This is, participants were reimbursed for participating. These circumstances were inevitable, since otherwise an interaction with a human would not be necessary or we would have infringed the common practice of reimbursing

participants. Future studies in actual learning settings like lectures or classrooms with reference to curriculum standards are therefore recommended.

Overall, it is interesting to note that social interdependence was positively correlated with our dependent measures indicating that perceiving a learning situation with a robot as more interdependent leads to higher intrinsic motivation, a better learning mood, higher self-efficacy and a more positive evaluation of the robot. It remains to be examined, though, how interdependence between human learners and educational robots can be successfully induced, and whether inducing interdependence with an educational robot generally contributes to a more positive learning experience.

Study 2 – Face-to-Face Interaction in Human-Robot Learning

The second study in the scope of cooperative learning is dedicated to face-to-face interaction. Direct face-to-face interaction between learning interactors has proven to be crucial for successful learning. Physical proximity promotes, for instance, direct exchange, problem-solving, or providing feedback among learners (Johnson & Johnson, 2009). However, several years ago the transition to technology-mediated learning increased the use of computers, accompanied by virtual agents as new interaction partners. On the other hand, the rise of educational robots makes direct face-to-face interaction with educational media possible. This development prompts the question on the implications of physical versus virtual embodiment for learning interactions. Following the assumptions by Norman (1988), physical objects constitute greater physical presence and thereby promote higher affordance. Arguing in line with Norman (1988), a physically embodied robot should imply to a greater extent how to use and interact with it than a virtually embodied character. Especially for educational robotics, this issue is of

particular relevance as it determines the success or failure of the introduction and dissemination of robots in educational environments. In the present study we attempted to explore the differences of direct interactions with a physically or a virtually embodied robot. We refer to a robot's tangible body by the term physical embodiment, while virtual embodiment refers to a simulated robot on a screen (see Wainer, Feil-Seifer, Shell, & Matarić, 2006; Ziemke, 2003).

To date, a number of studies have compared the effectiveness of embodiment in social interactions indicating that physically present robots were perceived more positively and trustworthy (Kidd & Breazeal, 2004; Wainer, Feil-Seifer, Shell, & Matarić, 2007), and led to better user performance compared to robots that were displayed digitally on a screen and compared to virtual agents (see Li (2015) for a review). Concerning embodiment in human-robot learning interactions, though, studies have revealed inconsistent results: For instance, most recent results did not generate significant differences regarding learning performance and the evaluation of the robot between a virtually and physically embodied robot (Kennedy, Baxter, & Belpaeme, 2015a; Rosenthal-von der Pütten, Straßmann, & Krämer, 2016). In contrast, previous results have indicated that the physical presence of a robot significantly increased learning gains and led to a better evaluation of the robotic learning partner compared to the virtual representation of the robot (Kose-Bagci, Ferrari, Dautenhahn, Syrdal, & Nehaniv, 2009; Leyzberg et al., 2012). Evidently, the results are ambiguous and do not allow clear conclusions about the preferable presentation of robots in learning interactions. Therefore, we aimed to address these inconsistent findings by re-examining the impact of a robot's physical vs. virtual embodiment on learning interactions. Beyond prior approaches, we assessed in addition to learning outcomes and the evaluation of the robot, participants' affective state. In particular, we evaluated intrinsic

motivation, learning mood, and self-efficacy—measures that have not been investigated comprehensively in previous works.

Hypotheses. Although previous findings point in different directions, we assumed—in line with Norman (1988)—that participants in the physical embodiment condition would have better learning outcomes (H2a), would report a more positive affective state (i.e., higher intrinsic motivation and self-efficacy, more positive learning mood; H2b), and would evaluate the robot more positively (i.e., higher educational impact, perceived usefulness, and more warmth and competence; H2c) compared to participants in the virtual embodiment condition.

Method

Participants. Participants were $N = 68$ German university students (34 female, 34 male) ranging in age from 18 to 65 years ($M = 25.51$, $SD = 6.20$).

Experimental conditions. We used a two-condition between-subject design and changed the embodiment of the robot. In the experimental condition participants interacted with the real, physically embodied NAO robot, while in the control condition participants were presented with a large monitor displaying the virtual NAO robot. With respect to size, the virtual robot was adjusted to the real NAO to avoid a possible effect of size as it was found that taller interactants can exert greater social influence (e.g., Huang, Olson, & Olson, 2002; Segura, Cramer, Gomes, Nylander, & Paiva, 2012).

Manipulation check. We checked whether our manipulation of robot embodiment (physical vs. virtual embodiment) had a significant effect on participants' perception of the robot's social presence. Originally, social presence has been defined as the "degree of salience of the other person in the interaction" (Short, Williams, & Christie, 1976, p. 65). With respect to technology-mediated learning, social presence represents a mental simulation of other

intelligences (Biocca, 1997), for instance, when people behave toward non-human agents as if they were real humans (Nass & Moon, 2000). By adapting *Social Presence* scales proposed by Harms and Biocca (2004) and Lee and colleagues (2006), we asked participants to indicate on a 7-point Likert scale (1 = *not at all*, 7 = *very much*) their impression of the social presence of their robotic interactant. By means of a 14-item questionnaire, participants could rate to what degree they feel connected to their robotic learning companion. An example item read: "While you were interacting with NAO, how much did you feel involved with it?".

Results

Preliminary analyses. First, we investigated descriptive statistics and internal consistencies (Cronbach's α) for all measures; the results are displayed in Table 3. With respect to reliabilities, all measures proved to be moderately reliable to reliable (α = .70 – .88). Subsequently, to examine the relation between our measures, we conducted a bivariate correlation analysis (Pearson's *r*) with our key study measures; the results are presented in Table 4. All dependent measures were moderately to highly intercorrelated (all *p*s < .05). Interestingly, learning mood was negatively correlated with the other dependent measures. That is, participants who indicated a more negative learning mood reported higher self-efficacy and intrinsic motivation, and perceived the robot to be more useful, attributed the robot more educational capabilities, higher warmth and competence, and social presence.

Manipulation check. To check the effectiveness of our manipulation, we conducted an independent sample *t*-test to compare participants' evaluation of the robot's social presence as a function of robot embodiment (virtual vs. physical embodiment). As expected, participants in the physical embodiment condition perceived the robot to be more socially present (*M* = 5.30, *SD* =

0.68) than in the virtual embodiment condition ($M = 4.74$, $SD = 0.83$), $t(66) = 3.01$, $p < .01$.

Thus, participants felt more socially connected to the real robot than to the virtual robot.

Hypotheses testing. With respect to our main hypotheses, we conducted a multivariate analysis of covariance (MANCOVA) to evaluate the impact of robot embodiment (physical vs. virtual embodiment) on learning outcomes (H2a), affective state (intrinsic motivation, learning mood, and self-efficacy; H2b), and the evaluation of the robot (educational capabilities, perceived usefulness, and warmth and competence; H2c), while controlling for technical affinity and prior experiences with the NAO robot. As anticipated, the MANCOVA demonstrated statistically significant differences between the two groups, $F(7,58) = 2.28$, $p = .04$, $\eta_p^2 = .22$.

Univariate analyses showed a statistically significant difference in learning outcome ($F(1,64) = 4.89$, p = .03, $\eta_p^2 = .07$), intrinsic motivation ($F(1, 64) = 5.49$, p = .02, $\eta_p^2 = .08$), educational capabilities ($F(1,64) = 5.44$, $p = .02$, $\eta_p^2 = .08$), and warmth and competence ($F(1,64) = 4.47$, $p = .04$, $\eta_p^2 = .07$) as a function of embodiment. The experimental manipulation had no significant impact on learning mood, self-efficacy, and perceived usefulness of the robot (all ps > .05). Sidak adjusted post-hoc tests revealed that participants who learned with the physically embodied robot reported significantly higher intrinsic motivation ($M = 5.17$, $SD = 0.76$) than participants who learned with the virtually embodied robot ($M = 4.77$, $SD = 0.67$; $p < .05$, $d = -0.56$). Likewise, respondents in the physical embodiment condition ascribed the robot more educational impact ($M = 4.77$, $SD = 0.84$) than participants in the virtual embodiment condition ($M = 4.30$, $SD = 0.90$; $p < .05$, $d = -0.54$). Regarding warmth and competence, participants in the physical embodiment condition perceived the robot as warmer and more competent ($M = 5.64$, $SD = 0.65$) than participants who interacted with the virtually embodied robot ($M = 5.29$, $SD = 0.80$; $p < .05$, $d = -0.48$). Contrary to our hypothesis (H2a), participants in the physical

embodiment condition had a lower learning performance (M = 4.73, SD = 2.37) than participants

in the virtual embodiment condition (M = 5.97, SD = 0.80; p < .05, d = 0.53).

Discussion

Embodiment in HRI is an extensively debated issue that has provided divergent results

which makes it difficult to draw a final conclusion. Due to these inconsistencies and following

the principle of direct face-to-face interaction in CL, we conducted an experimental study on the

influence of interacting with a physically vs. virtually embodied robot on learning performance,

affective state, and the evaluation of the robot.

We found that participants perceived greater social presence of the physically embodied

robot than of the virtual robot. Participants described the robot to be more communicative and

more focused on them during the interaction. It can be therefore assumed that physical presence

of a social robot indeed leads to greater affordance to interact and communicate with the robot.

We further observed significant differences in learning outcomes between participants who

interacted with the physical robot and those who interacted with the virtual robot—though, for

the benefit of the virtual robot. According to previous research (e.g., Kennedy et al., 2015a;

Rosenthal-von der Pütten et al., 2016), we argue that this outcome may be due to the novelty

effect. This is, the novel technology of the robot probably led participants to concentrate on the

robot and distracted them from the learning contents. This interpretation should be handled

cautiously as the novelty effect is also used to explain findings that are in favor of the impact of

physical robot embodiment on learning (e.g., Leyzberg et al., 2012). Thus, it remains to be

clarified in future work how a robot's novelty affects learning—if at all—and whether this effect

disappears in long-term interactions. Concerning robot evaluation, participants deemed the

physically present robot warmer and more competent, and ascribed it more educational

capabilities than the virtual robot. This finding is in line with prior results that suggested that physical presence of a robot can trigger a more positive evaluation of a robot's capabilities (e.g., Wainer et al., 2006, 2007; Fasola & Matarić, 2010). Finally, in terms of affective state, participants found the physically embodied robot to be more intrinsically motivating, but participants' self-efficacy and learning mood were not affected by robot embodiment. This outcome is somewhat surprising, as prior studies predominantly found that interacting with a physical robot is described more enjoyable (e.g., Kose-Bagci et al., 2009; Fasola & Matarić, 2010). Nevertheless, we have to point out that participants' learning mood was overall relatively neutral, which was probably due to the learning content itself that was possibly not appealing enough. To develop a full picture of the impact of robot embodiment on learning, additional studies in actual learning environments with recourse to real learning contents will be needed. Moreover, future research should investigate, among learning performance and the evaluation of the robot, learners' affective and motivational state as these determinants are crucial for successful learning. Taken together, our findings provide certain evidence for the positive effect of physical presence in HRI. We can exclude that the robot's external appearance, voice, or nonverbal behavior affected the learning interaction, as these factors were exactly identical in the physical vs. virtual embodiment conditions. Consequently, we can conclude that the physical collocation of a robotic learning partner contributes to a more positive perception of it and positively affects a learner's intrinsic motivation.

Study 3 – Social Support in Human-Robot Learning

After having clarified the role of social interdependence and face-to-face interaction in cooperative human-robot learning, the third study examined the influence of social support

provided by a robot on the learning experience. Social support is defined in a variety of ways, yet, generally having overlapping conceptualizations. The scientific community commonly highlights the provision of instrumental (e.g., financial assistance, material goods), informational (advice, useful information), or emotional (e.g., empathy, encouragement) support (e.g., Cohen, 2004; House, 1981), and emphasizes the importance of the social network allowing for communication and mutual assistance (Cobb, 1976; Wills, 1991). With regard to educational contexts, social support among peers has been shown to play a key role in student retention and success (e.g., DeBerard, Spielmans, & Julka, 2004; Grillo & Leist, 2013; Tinto, 1997). Building on the powerful effects of social support on learning, it seems not far-fetched applying it to HRI. Indeed, to date, several studies have investigated the impact of socially supportive behaviors provided by a robot (e.g., facial expressions and gestures, social dialogue, emotional support, etc.) on learning outcomes and the learning interaction (e.g., Leite, Castellano, Pereira, Martinho, & Paiva, 2014; Searbeck et al., 2010; Lubold, Walker, Pon-Barry, & Ogan, 2018). Evidence suggests that social support offered by a robot contributes to better learning outcomes (e.g., Lubold et al., 2018; Saerbeck et al., 2010), higher learning motivation (e.g., Saerbeck et al., 2010), or to more socially engaging behaviors toward a robot (e.g., Serholt & Barendregt, 2016). Further, it was found that children feel supported by a robot to a similar extent to what they feel supported by peers (Leite et al., 2014). However, these previous works have focused on elementary school children as target group, while no attention has been paid to robots providing social support in higher education. Addressing this issue, the present study relied back on social support in academic contexts. According to a theory proposed by Mazer (2008), student academic support encompasses direct assistance with course contents as well as emotional support provided by peers. Thompson and Mazer (2009a) focused on how students communicate

support and indicated that informational (e.g., provide useful information), esteem (e.g., increase others' self-esteem), motivational (e.g., motivate others to study), and venting (e.g., listen students' venting about classes or teachers) support are key components of student academic support. In building on this concept, we had a robot providing student academic support to undergraduates and evaluated the impact on students' learning gains, their affective state, and their perception of the robot.

Hypotheses. According to the theoretical implications, we hypothesized that participants in the social support condition would have better learning outcomes (H3a), would report a more positive affective state (i.e., higher intrinsic motivation and self-efficacy, more positive learning mood; H3b), and would evaluate the robot more positively (i.e., higher educational impact, perceived usefulness, and more warmth and competence; H3c) compared to participants in the neutral condition.

Method

Participants. Participants were $N = 70$ university students (36 female, 34 male) ranging in age from 18 to 48 ($M = 24.51$, $SD = 4.65$).

Experimental conditions. In a two-condition between-subject design we changed the social behavior of the robot by having socially supportive behavior in the experimental condition and neutral behavior in the control condition. To operationalize social support, we drew upon the theory of student academic support by Thompson (2008). Based on this classification, we manipulated *motivational, esteem* and *venting support*. The factor *informational support* was not considered in the present study as this would imply to withhold information or learning contents without which it would be impossible to learn. In the experimental condition the robot provided motivational support by encouraging participants to learn (e.g., "You accomplished this

demanding task very well. Let's start with the next task"). Contrary, in the neutral condition the robot provided sentences like: "This task is finished now. Let's start with the next task". Concerning esteem support, the robot complemented participants' work and acknowledged their effort (e.g., "Well done. That was a lot you had to remember") in the experimental condition, while the robot remained rather neutral in the control condition (e.g., "That was right. The task is finished now"). Finally, the robot offered venting support by acknowledging that other participants also experienced frustrations during the learning interaction (e.g., "It was not easy for other participants, too. You are not alone"). In the control condition, in turn, the robot expressed neutral statements on the learning (e.g., " I have already done this exercise with many other students").

Manipulation check. We assessed social support by adapting the Student Academic Support Scale proposed by Thompson and Mazer (2009a) to the learning interaction with the robot. The scale comprised 16 items that tapped participants' impression of the support the robot offered during the learning interaction (e.g., "NAO helped raise my confidence about the tasks").

Results

Preliminary analyses. Descriptive statistics and internal consistencies (Cronbach's α) for all measures are displayed in Table 5. Regarding reliabilities, all measures proved to be reliable to highly reliable ($\alpha = .80 - .92$). To examine the relation between our measures, we conducted a bivariate correlation analysis (Pearson's r) with our key study measures; the results are presented in Table 6. Our findings showed that all depended measures were positively intercorrelated (all ps < .01).

Manipulation check. We conducted an independent samples t-test to compare participants' perception of the robot's social support as a function of condition (supportive vs.

neutral condition). As expected, participants in the supportive condition perceived the robot to be more socially supportive ($M = 5.33$, $SD = 0.77$) than in the neutral condition ($M = 4.57$, $SD = 0.93$), $t(68) = 3.73$, $p < .001$. Indeed, participants perceived the robot in the social supportive condition to provide more social support than in the neutral condition.

Hypotheses testing. To evaluate the impact of condition (social supportive behavior vs. neutral behavior) on learning outcomes (H3a), affective state (intrinsic motivation, learning mood, and self-efficacy; H3b), and the evaluation of the robot (educational capabilities, perceived usefulness, and warmth and competence; H3c), we conducted a multivariate analysis of covariance (MANCOVA), while controlling for technical affinity and prior experiences with the NAO robot. Unexpectedly, the MANCOVA demonstrated no statistically significant differences between the two groups ($F(7,58) = 2.28$, $p = .04$, $\eta_p^2 = .22$). Contrary to our hypotheses (H3a to H3c), we found no differences between the experimental and the control condition on our dependent measures.

Discussion

Our research is the first to investigate how academic support provided by an educational robot influenced participants' learning outcomes and their learning experience. This is, we had the robot offer motivational support by encouraging students to learn, esteem support by acknowledging participants' effort, and venting support by admitting that other students experienced similar frustrations when learning ROILA. As expected, we found that participants perceived the robot in the supportive condition as more socially supportive than in the neutral condition. Regarding the impact of academic support on the learning experience, however, we found no significant differences between conditions. Participants had equal learning outcomes, and did not differ with respect to their affective state and their evaluation of the robot.

It seems that informational support—which we have provided in both conditions to enable the learning interaction at all—has a high significance across the four dimensions of academic support in HRI and possibly is deemed sufficient to support learning. Findings from educational psychological research support this assumption: Informational support was found to have the second highest importance among the dimensions while esteem support and motivational support were shown to be less important (Thompson & Mazer, 2009b). Venting support was ascribed the greatest importance (Thompson & Mazer, 2009b). In this process, the context has an important function. It is known that individuals who have a closer relationship to each other (e.g., friends), communicate more effectively academic support than less interrelated interaction partners (e.g., Thompson, 2008; Thompson & Mazer, 2009b). Additionally, a shared context between students is an essential aspect as students can better understand what their peers experience (Thompson, 2008). Probably herein lies the difficulty of implementing the four dimensions of student academic support into HRI. Namely, the difficulty of presenting the robot as an equal companion in the learning relationship that shares a common experience with the human learner. As a result, the socially supportive robot, albeit perceived to be more supportive, was not appreciated as a peer, thus not contributing to a more positively experienced learning interaction. Interestingly, our outcomes are contrary to that of Leite and colleagues (2014) who found that elementary school children preferred a robot offering esteem and motivational support over informational support. It may be the case that these variations are due to the different contexts as it is very likely that undergraduates place different expectations on how robots should support learning than younger children.

Generally, before evaluating our outcomes as having failed to comply the usefulness of the present approach, one ought to consider that the results clearly demonstrate which role

educational robots should take in cooperative learning processes in higher education. In fact, educational robots should be intended to facilitate learning activities by providing informational support in the first place. Beyond that, attention should be paid to use educational robots guiding group learning processes, and encouraging students to help and motivate each other. Consequently, to develop a full picture of how to efficiently implement academic support in HRI, additional studies will be needed that shift the focus toward multi-party learning interactions with a robot.

Study 4 – Group Processing in Human-Robot Learning

Closing the circle, the fourth study in the framework of cooperative learning in HRI focused on group processing. According to the approach of cooperative learning, effective cooperation can only exist when learners regularly reflect on their functioning and how they can improve the learning process (see Johnson, Johnson, & Smith, 2007). More precisely, the focus is on providing each other with feedback on what actions were helpful in achieving the learning goals and deciding about what behaviors to retain or to change (e.g., Johnson, Johnson, & Smith, 2007; Yager, Johnson, Johnson, & Snider, 1986). Educational research findings demonstrated that group processing was positively related to learning achievement (e.g., Yager et al., 1986; Johnson, Johnson, Stanne, & Garibaldi, 1989; Bertucci, Johnson, Johnson, & Conte, 2012).

So far, little work has been undertaken to investigate the effect of verbal feedback in human-robot learning activities. Yet, these studies have been mostly restricted to a robot providing corrective feedback on the learning contents, not the learning process itself. Further, inherently different feedback modalities have been applied making it difficult to draw meaningful conclusions about possible benefits of verbal feedback in human-robot learning.

Park, Kim, and del Pobil (2011), for instance, have explored the effects of positive, negative, and neutral feedback provided by a robot instructor on students' acceptance of the robot. Hardly surprising, participants evaluated the robot instructor more positively when it provided positive and neutral feedback compared to negative feedback. Likewise, participants were more likely to accept feedback by a robot instructor offering positive or neutral feedback. By having a robot providing either motivational feedback or feedback related to task performance, Schneider, Riether, Berger, and Kummert (2014) investigated a socially assistive robot's support in a mental rotation task. Findings showed that a robot giving performance related feedback led to higher task performance and a more positive evaluation of the task. In a more recent study, an interactive reinforcement learning framework was applied to design personalized training (Tsiakas, Abujelala, & Makedon, 2018). For this purpose, a robot provided either encouraging or challenging feedback. Results demonstrated that both feedback modalities facilitated robot personalization and contributed to higher task performance and engagement.

No former work, however, studied the effects of reflecting the interaction between humans and robots in an educational setting per se, and how implementing users' feedback into future robot behavior affects its evaluation. Additionally, previous approaches have not sufficiently focused on implementing sound theoretical concepts of feedback into learning settings. To this end, the fourth study aimed at incorporating the means of group processing in HRI. To do so, we had participants and the robot provide each other feedback on their learning interaction, and implemented participants' feedback for the second learning section. We explored how this affects participants' learning outcomes, affective state, and their evaluation of the robot.

Hypotheses. We hypothesized that participants in the group processing condition would have better learning outcomes (H4a), would report a more positive affective state (i.e., higher

intrinsic motivation and self-efficacy, more positive learning mood; H4b), and would evaluate the robot more positively (i.e., higher educational impact, perceived usefulness, and more warmth and competence; H4c) compared to participants in the control condition (no group processing). Furthermore, we expected an improvement with regard to the evaluation of the dependent measures in the experimental condition from time one to time two, while in the control condition no improvement should be recorded (H5).

Method

Participants. Participants were $N = 66$ university students (40 female, 26 male) ranging in age from 19 to 34 ($M = 24.55$, $SD = 3.24$).

Experimental conditions. In a two-condition between-subject design we included a feedback session of the learning interaction in the experimental condition, while in the control condition no feedback has been incorporated. Additionally, we applied a repeated-measures design by having participants interact with the robot in two consecutive learning sessions. In the experimental condition we had the robot providing participants feedback and, vice versa, encouraging participants to provide feedback to the robot. The main objective was to decide what actions were helpful and what behaviors to continue or to change for the second learning interaction. To do so, we followed the three steps of effective group processing (see Johnson, Johnson, & Holubec, 1994; Nam & Zellner, 2011): First, after the learning interaction had finished, we had the robot encouraging and instructing the feedback session. Afterwards, the robot gave participants feedback and, in turn, received their feedback. Third, the robot executed the feedback in the following learning interaction. We further evaluated the feedback procedure in a questionnaire. In the control condition, on the other hand, no feedback procedure was

included. The robot displayed in the second learning interaction the same verbal and non-verbal behavior as in the first learning session.

In order to provide effective feedback, we referred to a feedback model proposed by Hattie and Timperley (2007) that was developed to enhance learning. According to this model, feedback questions relate to four levels. First, the task performance level evaluates how well a task was accomplished (e.g., correct/ incorrect answers), and entails additional information. Second, the process level concerns the understanding how to do a task. Such feedback is oriented toward helping students to develop learning strategies, or detect errors. Third, the self-regulation level concerns the way students control and direct actions toward the learning goal. We excluded the self-regulation level from our manipulation as this involves metacognitive processes that a robot is not capable to influence. Finally, feedback on the self-level is more personal and entails little task-related information. Typically, it is geared toward expressing positive evaluations about the student and his or her learning efforts.

In detail, the robot introduced the feedback session and proposed three possible modifications of its interaction behavior. On the task level, the robot proposed participants to offer further information on the learning contents (e.g., more example sentences, reiteration of vocabulary). On the process level, the robot offered participants to use another learning strategy. This is, participants had the opportunity to use learning cards visualizing the grammar lessons and thereby activating visual learning. Ultimately, on the self-level, the robot suggested to motivate and praise participants efforts more or not to do it at all. Accordingly, depending on participants decisions, the second learning interaction could be adapted in eight various modes (e.g., no adaption at all, adaption on process and task level, adaption on all three levels, etc.).

We defined the feedback possibilities for participants a priori in order to ensure an effective implementation of their feedback. Offering participants free decision about what robot behaviors to continue or to change, could have made an implementation of participants' feedback substantially more difficult or even impossible.

Supplementary materials. Owing to the more complex design of the fourth study, we had a second learning interaction entailing additional learning materials (e.g., new vocabulary and grammar lessons). Further, we applied another measure to assess participants evaluation of the feedback session. For this purpose, we developed eight items to capture participants' evaluation of the group processing (e.g., "I think it is helpful for our learning to reflect the learning session with NAO"). The scale creation was partially based on items provided by Johnson, Johnson, Stanne, and Garibaldi (1989). Additionally, we assessed participants' commitment to realize the robot's feedback in the second learning interaction (e.g., "I have implemented NAO's feedback in the second learning session" and "I could implement NAO's feedback easily"). For reimbursing participants' efforts in the second learning interaction, they received a voucher worth € 10.

Results

Preliminary analyses. Descriptive statistics and internal consistencies (Cronbach's α) for all measures at time one and time two are displayed in Table 7. Regarding reliabilities, all measures proved to be reliable to highly reliable ($\alpha = .70 - .92$). To examine the relation between our measures, we conducted a bivariate correlation analysis (Pearson's r) with our key study measures; the results are presented in Table 8 for time 1 and in Table 9 for time 2. Our findings showed that all dependent measures were moderately to highly intercorrelated (all ps < .05).

Evaluation of the feedback session. In the experimental condition, participants reflected the learning interaction with the robot and had the option to change the robot's behavior for the second learning interaction on the task performance, process, or self-level. Approximately 13 percent of the participants decided not to change the robot's behavior at all, 42 percent favored a change on one level, while 45 participants preferred adaptations on two levels. Interestingly, no participant favored changes on the self-level, which means that participants decided the robot no to provide more or less motivational statements or praise. Nearly 72 percent wanted the robot to offer further information on the learning contents (task level), and 60 percent invited the robot to include the visual teaching strategy by offering learning cards (process level). To assess how participants evaluated the group processing with the robot, we conducted one sample t-tests against the neutral scale midpoint (scale value = 4 on a 7-point scale). Results showed that participants positively evaluated the feedback session at time one ($t(31) = 5.50$, $p < .001$, $d = 0.99$) and time two ($t(29) = 5.73$, $p < .001$, $d = 1.05$). Moreover, participants commitment to implement the robot's feedback in the second leaning session was found to be rather high, $t(29) = 10.46$, $p < .001$, $d = 1.91$.

Hypotheses testing. A repeated measures MANCOVA was conducted to test a possible effect of time and condition on the dependent measures, while controlling for technical affinity and prior experiences with the NAO robot. The results showed, however, that there was no significant change for the dependent measures over time, $F(6, 54) = 0.74$, $p = .62$, $\eta_p^2 = 0.08$. Moreover, there was no difference between the evaluation and the no evaluation conditions regarding our dependent measures, $F(6, 54) = 1.12$, $p = .37$, $\eta_p^2 = 0.11$, nor was there an interaction between time and condition, $F(6, 54) = 0.91$, $p = .50$, $\eta_p^2 = 0.09$.

Discussion

To date, no former work explored the impact of reflecting the learning process between a human and a robot per se, and how the implementation of a user's feedback in future robot behavior affects its evaluation. To this end, the fourth study aimed at incorporating the means of group processing, a feedback strategy to reflect learning processes, in HRI. In our human-robot learning scenario, we implemented a feedback session to reflect the functioning of the HRI. We found that participants perceived the feedback sessions positively, and demonstrated that participants requested the robot to adapt its behavior for future learning favorably at the task and process level. In particular, participants asked the robot to offer more information on the contents and to apply another teaching strategy. However, participants did not ask the robot to adapt its behavior on the self-level (e.g., more motivation and praise). Linking these outcomes to educational psychological literature, we find a similar pattern: That is, feedback was more effective when it informed about correct responses and how to change learning strategies based on previous trails, while praise appeared to be rather ineffective due to its limited relevance to the learning contents (see Hattie & Timperley (2007) for a review).

Contrary to our hypotheses, we did not observe an effect of providing and receiving feedback on participants' learning outcomes, affective state, and evaluation of the robot. Additionally, implementing participants' feedback in the robot's behavior for the second learning interaction did not affect the dependent measures either. Interestingly, however, we found that feedback was positively correlated with learning mood, intrinsic motivation, and self-efficacy indicating that a positive evaluation of the feedback session leads to a more positive learning mood, higher intrinsic motivation and higher self-efficacy. Likewise, evaluating the feedback

session more positively contributed to ascribing more educational capabilities to the robot, and perceiving it as more useful, warmer and more competent.

The reason for the limited results regarding our dependent measures is not clear, especially as they contradict previous findings that show a positive effect of feedback (e.g., Park et al., 2011; Schneider et al., 2014; Tsiakas et al., 2018), but it may have something to do with the artificiality of our learning task: Achieving the goal of learning ROILA vocabulary had no greater relevance for students. Thus, giving and receiving feedback—albeit positively acknowledged—to reach the assigned goal appeared to be rather ineffective. Support for this assumption provide the correlative results highlighting that feedback indeed can have positive effects on learning, motivation, and the perception of the robot companion. This is an important issue for future research that should (a) be conducted in the field (e.g., lectures, classrooms), with (b) actual learning activities that have greater significance for students, and (c) examine more closely the impact of assigned and self-set goals.

General Discussion

The main purpose of the present research was to investigate the applicability and effectiveness of a sophisticated educational approach, namely cooperative learning, in HRI in a programmatic manner. Cooperative learning is a strategy focusing on *how* students should interact with each other to enhance their learning outcomes and to impact the interaction between students positively. Essential components of cooperative learning such as social interdependence, direct face-to-face interaction, appropriate use of social skills, or group processing (Johnson & Johnson, 1989, 2009; Johnson et al., 1991) contribute to this purpose. The underlying idea of the present work aimed at taking advantage of the effectiveness of CL observed in human-human

interactions in order to shape human-robot learning activities effectively. To do so, we focused

on the following main research questions: First, is it possible to implement essential elements of

CL (viz., positive interdependence, direct face-to-face interaction, use of social skills, and group

processing) in a learning scenario with an educational robot? Second, which effects will these

elements have on students' performance, affective state, and the evaluation of the robot as a

learning companion?

      With respect to our first research question, our findings predominantly support the

applicability of CL in HRI: First, we found that students perceived a stronger social presence of a

physical robot in face-to-face interaction compared to a virtual robot. Second, participants

recognized the supportive robot compared to the neutral robot as more socially supportive. Third,

students appreciated the feedback session with the robot by evaluating the group processing

overall positively. However, an unexpected finding concerned our implementation of

interdependence: This is, participants in both conditions perceived the interaction with the robot

relatively interdependent. However, we do not believe that the dependence manipulation was too

weak, as we first successfully pretested our manipulation and second, it was stronger than others

used in HRI and HCI (e.g., Nass, Fogg, & Moon, 1996; Kim & Mutlu, 2014). Rather, we assume

that the general modality of the interaction in our learning scenario easily blurred the borders

between inter- and independence. Evidence for this theorizing provide the media equation

(Reeves & Nass, 1996) and the social agency theory (Moreno, Meyer, Spires, & Lester, 2001).

According to the media equation theory people tend to interact with communication technologies

in the same way they interact with humans (Reeves & Nass, 1996). Social agency theory further

postulates that applying verbal and visual social cues in communication technologies can

promote the development of a social partnership (Moreno et al., 2001). In our case, learning with

a robot in a team could be seen similar to learning with a human in a team, which resulted in accepting the robot as a social actor. This, in turn, probably contributed to establish a social partnership that was evaluated rather interdependent in both interactions.

On the second research question, we obtained fairly limited evidence for the effectiveness of CL in HRI. Concerning direct face-to-face interaction, participants found the physically embodied robot to be more intrinsically motivating, deemed it warmer and more competent, and ascribed it more educational capabilities than the virtual robot. This underlines the benefits educational robots can bring by being physically present in learning environments. On the one hand, the physical presence apparently led to greater affordance to interact with the robot. On the other hand, communicating directly with a real robot positively affected its evaluation as learning companion. Educational robots' physical presence, in contrast to their virtual display, can therefore contribute to their future usage in educational environments.

Unfortunately, our implementation of positive interdependence, social support, and group processing in HRI did not render significant outcomes. Interestingly, our findings are in line with results obtained by Kennedy, Baxter, and Belpaeme (2015b), who found that a robot that uses social behaviors in a collaborative learning interaction does not contribute to higher learning outcomes. Kennedy et al. (2015b) argue that while the physical presence of a robot contributes to learning gain, its social behavior is not a determining factor for successful learning. In contrast, we do not claim that a robots' physical presence is an exclusive candidate contributing to effective learning interactions with robots. Rather it seems that a robot's physical presence is, at present, one of the simplest ways to shape HRI in learning contexts. Concerning our findings, we assume that the artificial learning context and the temporal brevity of the interaction resulted in participants' low active engagement. Consequently, future work should be undertaken in real

learning settings like classrooms or lectures concentrating on actual learning contents that follow the curriculum. Further, to investigate the diverse nature of this approach properly, future studies should foster evaluating CL in multi-party interactions with an educational robot.

Conclusion

The educational landscape is always in flux and the current development of robotic technologies presents new challenges for education. Concurrently, researchers from pedagogy and psychology increasingly call for applying interdisciplinary approaches and theory-driven perspectives when tackling questions related to the usage of social robots (e.g., Alimisis, 2012; Eyssel, 2016). To account for this, we incorporated key elements of CL in HRI and investigated their effect on the learning interaction.

In view of the rather limited results regarding the effectiveness of our manipulations on the dependent measures, one could argue that CL is not applicable in the context of HRI. We support nevertheless the idea that CL can be successfully implemented in HRI, when considering certain aspects such as use in real contexts, multi-party interactions with educational robots, or long-term applications in future work. Taken together, we have provided various theory-based strategies how to induce CL with an educational robot. These were, for instance, the manipulation of positive interdependence via task, goal, and reward interdependence (Johnson & Johnson, 1989, 2009; Wageman, 2001), the application of academic support strategies (Thompson, 2008), or the implementation of an elaborated feedback model for enhanced learning (Hattie & Timperley, 2007) in our human-robot learning interactions. Although the effectiveness of our approach was limited, we still argue that adopting theoretical approaches into HRI and experimentally evaluating their effectiveness will forward research in this field to

higher levels. Even more important, though, future learners and teachers will benefit from such endeavors.

Ethical Standard. Our research is approved by the ethics committee of Bielefeld University. We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study.

References

Alimisis, D. (2012). Robotics in education & education in robotics: Shifting focus from technology to pedagogy. *Proceedings of the 3rd International Conference on Robotics in Education* (RiE 2012, Prague), 7–14.

Alimisis, D. (2013). Educational robotics: Open questions and new challenges. *Themes in Science & Technology Education, 6*(1), 63–71.

Arras, K. O. & Cerqui, D. (2005). Do we want to share our lives and bodies with robots? A 2000-people survey (Report No. 0605–001), Lausanne: Autonomous systems lab, Swiss federal institute of technology, 1–38.

Bainbridge, W.A., Hart, J.W., Kim, E.S., & Scassellati, B. (2011). The Benefits of Interactions with Physically Present Robots over Video-Displayed Agents. *International Journal of Social Robotics, 3*(1), 41–52.

Bartneck, C. (2003) Interacting with an embodied emotional character. *Proceedings of the 16th International Conference on Designing Pleasurable Products and Interfaces* (DPPI 2003, Pittsburgh, PA), 55–60.

Bartneck, C., Suzuki, T., Kanda, T., & Nomura, T. (2006). The influence of people's culture and prior experiences with Aibo on their attitude towards robots. *AI & Society, 21*(1), 217–230.

Baxter, P., Wood, R., Baroni, I., Kennedy, J., Nalin, M., & Belpaeme, T. (2013). Emergence of turn-taking in unstructured child-robot social interactions. *Proceedings of the 8th International Conference on Human-Robot Interaction* (HRI 2013, Tokyo), 77–78.

Baylor, A. & Ryu, J. (2003). The API (Agent Persona Instrument) for assessing pedagogical agent persona. In D. Lassner & C. McNaught (Eds.), *Proceedings of EdMedia: World*

Conference on Educational Media and Technology 2003 (pp. 448–451). Honolulu, Hawaii: AACE Press.

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

Bertucci, A., Johnson, D. W., Johnson, R. T. Conte, S. (2012). Influence of group processing on achievement and perception of social and academic support in elementary inexperienced cooperative learning groups. *The Journal of Educational Research, 105*(5), 329–335.

Biocca, F. (1997). The cyborg's dilemma: Progressive embodiment in virtual environments. *Journal of Computer-Mediated Communication, 3*(2), 1–29.

Catlin, D., & Blamires, M. (2010). The principles of Educational Robotic Applications (ERA): A framework for understanding and developing educational robots and their activities. In J. Clayson, J. & I. Kalaš (Eds.), *Constructionist approaches to creative learning, thinking and education: Lessons for the 21st century. Proceedings of the Constructionism 2010 Conference*. Paris: American University of Paris.

Cobb, S. (1976). Social support as a moderator of life stress. *Psychosomatic Medicine, 38*(5), 300–314.

Cohen, S. (2004). Social relationships and health. *American Psychologist, 59*(8), 676–684.

DeBerard, M. S., Spielmans, G. I., & Julka, D C. (2004). Predictors of academic achievement and retention among college freshmen: A longitudinal study. *College Student Journal, 38*(1), 66–80.

Deci, E. L. & Ryan, R. M. (2003). Intrinsic motivation inventory. Retrieved from http://www.selfdeterminationtheory.org/questionnaires/10-questionnaires/50

Denis, B., & Hubert, S. (2001). Collaborative learning in an educational robotics environment. *Computers in Human Behavior, 17*(5-6), 465–480.

Deutsch, M. (1949). A theory of cooperation and competition. *Human Relations, 2,* 129–152.

Deutsch, M. (1962). Cooperation and trust: Some theoretical notes. In M.R. Jones (Ed.), *Nebraska Symposium on Motivation* (pp. 275–319). Lincoln, NE: University of Nebraska Press.

Eyssel, F. (2017). An experimental psychological perspective on social robotics. *Robotics and Autonomous Systems, 87*, 363–371.

Fasola, J., & Matarić, M.J. (2010). A socially assistive robot exercise coach for the elderly. *Journal of Human–Robot Interaction, 1*(1), 1–16.

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. 2007. G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods, 39*, 175–191.

Fischer, K., Lohan, K., Saunders, J., Nehaniv, C., Wrede, B., & Rohlfing, K. (2013). The impact of the contingency of robot feedback on HRI. *Proceedings of the International Conference on Collaboration Technologies and Systems* (CTS 2013, San Diego, USA).

Fiske, S. T., Cuddy, A. J. C., Glick. P., & Xu, J. 2002. A model of (often mixed) stereotype content: Competence and warmth respectively follow from perceived status and competition. *Journal of Personality and Social Psychology, 82*(6), 878–902.

Gibson, W. (1996, July 03). The Site-Seers' Guide to Some Way-Out Internet Futures. *The Washington Post*, p. A1.

Gouldner, A. W. (1960). The norm of reciprocity: A preliminary statement. *American Sociological Review, 25*, 161–178.

Grillo, M. C., & Leist, C. W. (2013). Academic support as a predictor of retention to graduation: New insights on the role of tutoring, learning assistance, and supplemental instruction. *Journal of College Student Retention: Research, Theory & Practice, 15*(3), 387–408.

Han, J., Jo, M., Park, S., & Kim, S. (2005) The educational use of home robots for children. *Proceedings of the 14th International Symposium on Robot and Human Interactive Communication* (RO-MAN 2005, Nashville), 378–383.

Harms, C., & Biocca, F. (2004). Internal consistency and reliability of the networked minds social presence measure. *Proceedings of the 7th Annual International Workshop on Presence* (ISPR 2004, Valencia, Spain), 246–251.

Hattie, J. & Timperley, H. (2007). The power of feedback. *Review of Educational Research, 7*(1), 81–112.

Hidi, S., & Harackiewicz, J. M. (2000). Motivating the academically unmotivated: A critical issue for the 21st century. *Review of Educational Research, 70*(2), 151–179.

House, J.S. (1981). Work stress and social support. Reading, MA: Addison-Wesley.

Huang, C.-M. & Mutlu B. (2012). Robot behavior toolkit: Generating effective social behaviors for robots. *Proceedings of the 7th International Conference on Human-Robot Interaction* (HRI 2012, Massachusetts), 25–32.

Huang, C.-M. & Mutlu B. (2013). Modeling and evaluating narrative gestures for humanlike robots. *Proceedings of the Robotics: Science and Systems Conference*, (RSS 2013, Berlin, Germany).

Huang, C.-M. & Mutlu B. (2014). Multivariate evaluation of interactive robot systems. *Autonomous Robots, 37*(4), 335–349.

Huang, W., Olson, J. S., & Olson, G. M. (2002, April). Camera angle affects dominance in video-mediated communication. *Proceedings of the 2002 Conference on Human Factors in Computing Systems* (CHI 2002, Minneapolis), 716–717.

Johnson, D. W. (2009). *Reaching out: Interpersonal effectiveness and self-actualization* (10th ed.). Boston: Allyn & Bacon.

Johnson, M., Bradshaw, J.M., Feltovich, P.J., Hoffman, R.R., Jonker, C., van Riemsdijk, M.B., & Sierhuis, M. (2011). Beyond cooperative robotics: The central role of interdependence in coactive design. *Intelligent Systems, 26*(3), 81–88.

Johnson, M., Bradshaw, J.M., Feltovich, P.J., Jonker, C.M., van Riemsdijk, M.B., & Sierhuis, M. (2014). Coactive design: Designing support for interdependence in joint activity. *Journal of Human-Robot Interaction, 3*(1), 43–69.

Johnson, D. W., & Johnson, R. T. (1989). *Cooperation and competition, theory and research*. Minneapolis, MN: Interaction Book Company.

Johnson, D. W., & Johnson, R.T. (1992). *Positive interdependence: Activity manual and guide*. Edina, MN: Interaction Book Company.

Johnson, R. T., & Johnson, D. W. (1994). An overview of cooperative learning. In J. S. Thousand, R. A. Villa, & A. I. Nevin (Eds.), *Creativity and collaborative learning: A practical guide to empowering students and teachers* (pp. 31–44). Baltimore, MD: Paul H. Brookes.

Johnson, D. W. & Johnson, R. T. (1999). *Learning together and alone: Cooperative, competitive, and individualistic learning* (5th ed.). Boston: Allyn & Bacon.

Johnson, D. W. & Johnson, R. (2005). New developments in social interdependence theory. *Psychology Monographs, 131*, 285–358.

Johnson, D. W. & Johnson, R. T. (2009). An educational psychology success story: Social interdependence theory and cooperative learning. *Educational Researcher, 38*(5), 365–379.

Johnson, D. W., Johnson, R. T., & Holubec, E. (1994*). The new circles of learning. Cooperation in the classroom and school.* Alexandria, Virginia: Association for Supervision and Curriculum Development.

Johnson, D. W., Johnson, R. T., & Smith, K. A. (1991). Cooperative learning: Increasing college faculty instructional productivity (Report No. 4), Washington: George Washington University.

Johnson, D. W., Johnson, R.T., & Smith, K. (2007). The state of cooperative learning in postsecondary and professional settings. *Educational Psychology Review, 19*(1), 15–29.

Johnson, D. W., Johnson, R. T., Stanne, M. B., & Garibaldi, A. (1989). Impact of group processing on achievement in cooperative groups. *The Journal of Social Psychology, 130*(4), 507–515.

Kelley, J. F. (1984). An iterative design methodology for user-friendly natural language office information applications. *ACM Transactions on Information Systems, 2*(1), 26–41.

Kelley, H.H., Kerr, N.L., Reis, H.T., Holmes, J.W., Rusbult, C.E., & van Lange, P.A.M. (2003). *An atlas of interpersonal situations.* Cambridge: Cambridge University Press.

Kennedy, J., Baxter, P., & Belpaeme, T. (2015a). Comparing robot embodiments in a guided discovery learning interaction with children. *International Journal of Social Robotics, 7*(2), 293–308.

Kennedy, J., Baxter, P., & Belpaeme, T. (2015b). The robot who tried too hard: Social behaviour of a robot tutor can negatively affect child learning. *Proceedings of the International*

Conference *on Human-Robot Interaction*, (HRI 2015, Portland, USA), 67–74. Kidd, C.D., & Breazeal, C.L. (2004) Effect of a robot on user perceptions. *Proceedings of the International Conference on Intelligent Robots and Systems* (IROS 2004, Sendai, Japan), 3559–3564.

Kim, Y., & Mutlu, B. (2014). How social distance might shape human-robot collaboration. *International Journal of Human-Computer Studies, 72*(12), 783–795.

Kose-Bagci, H., Ferrari, E., Dautenhahn, K., Syrdal, D. S., Nehaniv, C. L. (2009). Effects of embodiment and gestures on social interaction in drumming games with a humanoid robot. *Advanced Robotics, 23*(14), 1951–1996.

Köse, H., Uluer, P., Akalın, N., Yorgancı, R., Özkul, A., & Ince, G. (2015). The effect of embodiment in sign language tutoring with assistive humanoid robots. *International Journal of Social Robotics 7*(4), 537–548.

Krämer, N.C. (2008). Soziale Wirkungen virtueller Helfer. Gestaltung und Evaluation von Mensch-Computer-Interaktionen. Stuttgart: Kohlhammer.

Krämer, N., Simons, N., and Kopp, S. (2007). The effects of an embodied conversational agent's nonverbal behavior on user's evaluation and behavioral mimicry. *Lecture Notes in Computer Science, 4722*, 238–251.

Lea, S. J., Stephenson, D., & Troy, J. (2003). Higher education students' attitudes to student-centred learning: Beyond 'educational bulimia'? *Studies in Higher Education, 28*(3), 321–334.

Lee, K. M., Jung, Y., Kim, J., & Kim, S. R. (2006). Are physically embodied social agents better than disembodied social agents?: The effects of physical embodiment, tactile interaction,

and people's loneliness in human–robot interaction. *International Journal of Human-Computer Studies, 64*(10), 962–973.

Leite, I., Castellano, G., Pereira, A., Martinho, C., & Paiva, A. (2014). Empathic robots for long-term interaction. evaluating social presence, engagement and perceived support in children. *International Journal of Social Robotics, 6*(3), 329–341.

Leite, I., Martinho, C., Pereira, A., & Paiva, A. (2009). As time goes by: Long-term evaluation of social presence in robotic companions. *Proceedings of the 18th International Symposium on Robot and Human Interactive Communication* (RO-MAN 2009, Toyama, Japan), 669–674.

Lemaignan, S., Jacq, A., Hood, D., Garcia, F., Paiva, A., & Dillenbourg, P. (2016) Learning by teaching a robot: The case of handwriting. *IEEE Robotics & Automation Magazine, 23*(2), 56–66.

Leyzberg, D., Spaulding, S., Toneva, M., & Scassellati, B. (2012). The physical presence of a robot tutor increases cognitive learning gains. *Proceedings of the 34th Annual Conference of the Cognitive Science Society* (CogSci 2012, Austin, TX), 1882–1887.

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.

Lubold, N., Walker, E., Pon-Barry, H. & Ogan, A. (2018). Automated pitch convergence improves learning in a social, teachable robot for middle school mathematics. *Proceedings of the 19th International Conference on Artificial Intelligence in Education* (AIED 2018, London), 282–296.

Miller D.P., & Nourbakhsh I.R. (2016) Robotics for education. In B. Siciliano & O. Khatib (Eds), *Springer Handbook of Robotics* (pp. 2115–2134). Berlin, Heidelberg: Springer.

Miller, D.P., Nourbakhsh, I.R., & Siegwart, R. (2008). Robots for Education. In B. Siciliano & O. Khatib (Eds), *Springer Handbook of Robotics* (pp. 1283–1301). Berlin, Heidelberg: Springer.

Mitnik, R., Nussbaum, M., & Soto, A. (2008). An autonomous educational mobile robot mediator. *Autonomous Robots 25*(4), 367–382.

Moreno, R., Mayer, R. E., Spires, H. A., & Lester, J. C. (2001). The case for social agency in computer-based teaching: Do students learn more deeply when they interact with animated pedagogical agents? *Cognition and Instruction, 19*(2), 177–213.

Mubin, O., Bartneck, C., Feijs, L., Hooft van Huysduynen, H., Hu, J., & Muelver, J. (2012). Improving Speech recognition with the robot interaction language (ROILA). *Journal of Disruptive Science and Technology, 1*(2), 79–88.

Mubin, O., Henderson, J., & Bartneck, C. (2013). Talk ROILA to your Robot. *Proceedings of the 15th ACM International Conference on Multimodal Interaction* (ICMI 2013, Sydney), 317–318.

Nam, C.W. & Zellner, R.D. (2011). The relative effects of positive interdependence and group processing on student achievement and attitude in online cooperative learning. *Computers & Education, 56*(3), 680–688.

Nass, C., Fogg, B. J., & Moon, Y. (1996). Can computers be teammates? *International Journal on Human-Computer Studies, 45*(6), 669–678.

Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues, 56*(1), 81–103.

Neyer, F. J., Felber, J., & Gebhardt, C. (2012). Entwicklung und Validierung einer Kurzskala zur Erfassung von Technikbereitschaft (technology commitment) [Development and validation of a short technology commitment scale]. *Diagnostica, 58,* 87–99.

Norman, D.A. (1988). *The psychology of everyday things.* New York: Basic Books.

Papert, S. (1980). *Mindstorms: children, computers, and powerful ideas*. New York: Basic Books.

Park, E., Kim, K. J., & del Pobil, A. P. (2011). The effects of a robot instructor's positive vs. negative feedbacks on attraction and acceptance towards the robot in classroom. *Proceedings of the 3rd International Conference on Social Robotics* (ICSR 2011, Amsterdam, The Netherlands), 135–141.

Piaget, J. (1954). *The construction of reality in the child* (M. Cook, Trans.). New York: Basic Books.

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the motivated strategies for learning questionnaire (Mslq). *Educational and Psychological Measurement, 53*(3), 801–813.

Putnam, J., Rynders, J., Johnson, R., & Johnson, D. W. (1989). Collaborative skills instruction for promoting positive interactions between mentally handicapped and nonhandicapped children. *Exceptional Children, 55*(6), 550–557.

Ramachandran, A., Huang, C.-M., Gartland, E, &. Scassellati, B. (2018). Thinking aloud with a tutoring robot to enhance learning. *Proceedings of the 13th International Conference on Human-Robot Interaction* (HRI 2018, Chicago, USA), 59–68.

Reich, N. & Eyssel, F. (2013). Attitudes towards service robots in domestic environments: The role of personality characteristics, individual interests, and demographic variables. *Journal of Behavioral Robotics, 4,* 123–130.

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,* 875–888.

Reeves, B., & Nass, C. (1996). *The media equation: how people treat computers, television, and new media like real people and places*. Chicago: The Center for the Study of Language and Information Publications.

Rosenthal-von der Pütten, A. M., Straßmann, C., & Krämer, N. C. (2016). Robots or agents – neither helps you more or less during second language acquisition. *Lecture Notes in Computer Science, 10011*, 256–268.

Šabanović, S. Berry, C. A., & Bethel, C.L. (2017). Introduction to journal of human-robot interaction special issue on HRI education. *Journal of Human-Robot Interaction, 6*(2), 1–2.

Saerbeck, M., Schut, T., Bartneck, C., & Janse, M.D. (2010). Expressive robots in education: Varying the degree of social supportive behavior of a robotic tutor. *Proceedings of the Conference on Human Factors in Computing Systems* (CHI 2012, Atlanta, Georgia), 1613–1622.

Salem, M., Kopp, S., Wachsmuth, I., Rohlfing, K.J., & Joublin, F. (2012). Generation and evaluation of communicative robot gesture. *International Journal of Social Robotics, 4*, 201–217.

Schneider, S., Riether, N., Berger, I., & Kummert, F. (2014). How socially assistive robots supporting on cognitive tasks perform. *Proceedings of the 50th Anniversary Convention on Artificial Intelligence and Simulation for Behaviour* (AISB 2014, London, UK), 1–6.

Segura, E. M., Cramer, H., Gomes, P.F., Nylander, S., & Paiva, A. (2012) Revive!: Reactions to migration between different embodiments when playing with robotic pets. *Proceedings of the 11th International Conference on Interaction Design and Children* (IDC 2012, Bremen, Germany), 88–97.

Serholt, S., & Barendregt, W. (2016). Robots tutoring children: longitudinal evaluation of social engagement in child-robot interaction. *Proceedings of the 9th Nordic Conference on Human-Computer Interaction* (NordiCHI 2016, Gothenburg, Sweden), 64-1–64-10.

Short, J., Williams, E., & Christie, B. (1976). *The social psychology of telecommunications*. New York: Wiley.

Slavin, R. E. (1992). When and why does cooperative learning increase achievement? Theoretical and empirical perspectives. In R. Hertz-Lazarowitz & N. Miller (Eds.), *Interaction in cooperative groups: The theoretical anatomy of group learning* (pp. 145–173). New York: Cambridge University Press.

Slavin, R. E. (1996). Research on cooperative learning and achievement: What we know, what we need to know. *Contemporary Educational Psychology, 21*(1), 43–69.

Szafir, D., & Mutlu, B. (2012). Pay attention! Designing adaptive agents that monitor and improve user engagement. *Proceedings of the Conference on Human Factors in Computing Systems* (CHI 2012, Austin, USA), 11–20.

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.

Thompson, B. (2008). How college freshman communicate student academic support: A grounded theory study. *Communication Education, 57*(1), 123–144.

Thompson, B., & Mazer, J. P. (2009a). Student academic support: A validity test. *Communication Research Reports, 28*(3), 214–224.

Thompson, B., & Mazer, J. P. (2009b). College student ratings of student academic support: Frequency, importance, and modes of communication. *Communication Education, 58*(3), 433–458.

Tiberius, R., & Billson, J. (1993). The social context of teaching and learning. *New Directions for Teaching and Learning, 45*, 67–86.

Tinto, V. (1997). Classrooms as communities: Exploring the educational character of student persistence. *Journal of Higher Education, 68*(6), 599–623.

Tsiakas, K., Abujelala, M., & Makedon, F. (2018). Task engagement as personalization feedback for socially-assistive robots and cognitive training. *Technologies, 6*(2), 1–17.

Wageman, R. (2001). The meaning of interdependence. In M. E. Turner (Ed.), *Groups at work. Theory and research* (pp. 197–217). Mahwah, NJ: Erlbaum.

Wageman, R., & Baker, G. (1997). Incentives and cooperation: The joint effects of task and reward interdependence on group performance. *Journal of Organizational Behavior, 18*, 139–158.

Wagner, A.R., & Arkin, R.C. (2006). A framework for situation-based social interaction. *Proceedings of the 15th International Symposium on Robot and Human Interactive Communication* (RO-MAN 2006, Hatfield, UK), 291–297.

Wainer, J., Feil-Seifer, D.J., Shell, D.A., & Matarić, M.J. (2006). The role of physical embodiment in human-robot interaction. *Proceedings of the 15th International Symposium on Robot and Human Interactive Communication* (RO-MAN 2006, Hatfield, UK), 117–122.

Wainer J., Feil-Seifer, D.J., Shell, D.A., & Matarić, M.J. (2007). Embodiment and human-robot interaction: A task-based perspective. *Proceedings of the 16th International Symposium on Robot and Human Interactive Communication* (RO-MAN 2007, Jeju, South Korea), 872–877.

Weldon, E., & Weingart L. (1993). Group goals and group performance. *British Journal of Social Psychology, 32*, 307–334.

Werfel, J. (2013). Embodied teachable agents: Learning by teaching robots. *Proceedings of the 13th International Conference on Intelligent Autonomous Systems,* (IAS 2013, Padova, Italy), 1–8.

Wilde, M., Bätz, K., Kovaleva, A., & Urhahne, D. (2009). Überprüfung einer Kurzskala intrinsischer Motivation (KIM) [Testing a short scale of intrinsic motivation]. *Zeitschrift für Didaktik der Naturwissenschaften, 15*, 31–45.

Wills, T.A. (1991). Social support and interpersonal relationships. In M.S. Clark (Ed.), *Prosocial behavior* (pp. 265–289). Newbury Park, CA: Sage.

Yager, S., Johnson, R.T., Johnson, D.W., & Snider, B. (1986). the impact of group processing on achievement in cooperative learning groups. *The Journal of Social Psychology, 126*(3), 389–397.

Yousuf, A.M. (2009). Robots in education. In J. Rabuñal Dopico, J. Dorado, & A. Pazos (Eds.), *Encyclopedia of artificial intelligence* (pp. 1383-1388). Hershey, PA: IGI Global.

Ziemke, T. (2003). What's that thing called embodiment? *Proceedings of the 25th Annual Meeting of the Cognitive Science Society* (CogSci 2003, Boston, Massachusetts), 1305–1310.

Table 1

Descriptive Statistics and Internal Consistencies of the Dependent Measures (Study 1)

Measure	*M*	*SD*	Min	Max	α
Learning Mood	5.40	0.90	3.20	6.90	.83
Intrinsic Motivation	4.65	1.05	2.67	6.78	.84
Self-Efficacy	4.70	1.30	2.40	7.00	.86
Perceived Usefulness	5.01	1.19	1.67	7.00	.94
Educational Capabilities	4.58	1.17	2.21	7.00	.92
Warmth and Competence	5.56	0.85	3.67	7.00	.90
Social Interdependence	5.05	1.01	3.10	7.00	.87

Table 2

Correlations Among Dependent Measures (Study 1)

Measure	Learn. Mood	Intrin. Mot.	Self-Eff.	Perc. Use.	Educ. Capa.	Warm. Com.	Soc. Inter.
Learn. Mood		.83**	.68**	.74**	.60*	.62**	.61**
Intrin. Mot.			.82**	.62**	.56**	.56**	.59**
Self-Eff.				.53**	.37**	.47**	.51**
Perc. Use.					.76**	.73**	.67**
Educ. Capa.						.84**	.69**
Warm. Com.							.77**
Soc. Inter.							

Note. Learn. Mood = learning mood. Intrin. Mot. = intrinsic motivation. Self–Eff. = self-efficacy. Perc. Use. = perceived usefulness. Educ. Capa. = educational capabilities. Warm. Com. = warmth and competence. Soc. Inter. = social interdependence. * $p < .05$. ** $p < .01$.

Table 3

Descriptive Statistics and Internal Consistencies of the Dependent Measures (Study 2)

Measure	*M*	*SD*	Min	Max	α
Learning Mood	3.15	0.62	2.20	5.20	.81
Intrinsic Motivation	4.96	0.74	3.33	6.33	.70
Self-Efficacy	5.00	1.03	2.00	7.00	.75
Perceived Usefulness	5.17	0.89	3.13	6.87	.88
Educational Capabilities	4.53	0.90	2.29	6.29	.85
Warmth and Competence	5.46	0.75	3.00	7.00	.83
Social Presence	5.02	0.81	3.14	6.43	.84

Table 4

Correlations Among Dependent Measures (Study 2)

Measure	Learn. Mood	Intrin. Mot.	Self-Eff.	Perc. Use.	Educ. Capa.	Warm. Com.	Soc. Pres.
Learn. Mood		-.74**	-.48**	-.57**	-.38**	-.39**	-.47**
Intrin. Mot.			.60**	.48**	.28*	.40**	.39**
Self-Eff.				.48**	.29*	.35**	.45**
Perc. Use.					.63**	.53**	.67**
Educ. Capa.						.70**	.75**
Warm. Com.							.70**
Soc. Pres.							

Note. Learn. Mood = learning mood. Intrin. Mot. = intrinsic motivation. Self–Eff. = self-efficacy. Perc. Use. = perceived usefulness. Educ. Capa. = educational capabilities. Warm. Com. = warmth and competence. Soc. Pres. = social presence.
* *p* < .05. ** *p* < .01.

Table 5

Descriptive Statistics and Internal Consistencies of the Dependent Measures (Study 3)

Measure	*M*	*SD*	Min	Max	α
Learning Mood	5.22	1.04	2.60	6.90	.86
Intrinsic Motivation	4.70	0.91	2.56	6.67	.80
Self-Efficacy	4.65	1.06	2.00	6.80	.80
Perceived Usefulness	4.93	1.01	2.27	6.80	.92
Educational Capabilities	4.55	0.93	2.29	6.29	.87
Warmth and Competence	5.56	0.81	2.92	7.00	.89
Social Support	4.93	0.94	2.69	6.81	.89

Table 6

Correlations Among Dependent Measures (Study 3)

Measure	Learn. Mood	Intrin. Mot.	Self- Eff.	Perc. Use.	Educ. Capa.	Warm. Com.	Soc. Sup.
Learn. Mood		.74**	.41**	.60**	.35**	.44**	.38**
Intrin. Mot.			.70**	.66**	.47**	.52**	.52**
Self-Eff.				.65**	.46**	.46**	.49**
Perc. Use.					.70**	.71**	.70**
Educ. Capa.						.78**	.71**
Warm. Com.							.70**
Soc. Sup.							

Note. Learn. Mood = learning mood. Intrin. Mot. = intrinsic motivation. Self–Eff. = self-efficacy. Perc. Use. = perceived usefulness. Educ. Capa. = educational capabilities. Warm. Com. = warmth and competence. Soc. Sup. = social support.
** *p* < .01.

Table 7

Descriptive Statistics and Internal Consistencies of the Dependent Measures at Time 1 and Time 2 (Study 4)

Measure	Time 1		Time 2		Time 1		Time 2		Time 1	Time 2
	M	*SD*	*M*	*SD*	Min	Max	Min	Max	α	
Learning Mood	5.70	0.67	5.65	0.78	4.10	6.89	3.80	7.00	.70	.82
Intrinsic Motivation	4.88	0.94	5.08	0.98	2.56	6.56	2.56	7.00	.82	.83
Self-Efficacy	4.73	1.30	4.99	1.22	1.60	7.00	1.80	7.00	.89	.88
Perceived Usefulness	5.22	0.96	5.16	1.06	3.13	7.00	2.60	6.87	.91	.92
Educational Capabilities	4.69	0.90	4.52	1.02	2.43	6.64	2.00	6.50	.88	.91
Warmth and Competence	5.70	0.67	5.49	0.79	4.42	7.00	3.25	6.83	.84	.89
Feedback (only exp. cond. *n* = 32)	5.16	1.20	5.18	1.13	2.75	7.00	3.13	6.88	.86	.83

Table 8

Correlations Among Dependent Measures at Time 1 (Study 4)

Measure	Learn. Mood	Intrin. Mot.	Self-Eff.	Perc. Use.	Educ. Capa.	Warm. Com.	Feedback
Learn. Mood		.81**	.52**	.66**	.35**	.41**	.72**
Intrin. Mot.			.67**	.70**	.43**	.48**	.63**
Self-Eff.				.59**	.36**	.34**	.40*
Perc. Use.					.65**	.62**	.73**
Educ. Capa.						.80**	.59**
Warm. Com.							.62**
Feedback							

Note. Learn. Mood = learning mood. Intrin. Mot. = intrinsic motivation. Self–Eff. = self-efficacy. Perc. Use. = perceived usefulness. Educ. Capa. = educational capabilities. Warm. Com. = warmth and competence. Soc. Sup. = social support. * $p < .05$, ** $p < .01$.

Table 9

Correlations Among Dependent Measures at Time 2 (Study 4)

Measure	Learn. Mood	Intrin. Mot.	Self-Eff.	Perc. Use.	Educ. Capa.	Warm. Com.	Feedback
Learn. Mood		.78**	.46**	.66**	.51**	.56**	.58**
Intrin. Mot.			.71**	.63**	.51**	.47**	.56**
Self-Eff.				.40**	.27*	.26*	.43*
Perc. Use.					.72**	.70**	.76**
Educ. Capa.						.85**	.73**
Warm. Com.							.63**
Feedback							

Note. Learn. Mood = learning mood. Intrin. Mot. = intrinsic motivation. Self–Eff. = self-efficacy. Perc. Use. = perceived usefulness. Educ. Capa. = educational capabilities. Warm. Com. = warmth and competence. Soc. Sup. = social support. * $p < .05$. ** $p < .01$.