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I Like My Relational Machine Teacher: An AI Instructor's Communication Styles and Social Presence in Online Education

Jihyun Kim[a], Kelly Merrill Jr.[b], Kun Xu[c], and Deanna D. Sellnow[a]

[a]Nicholson School of Communication and Media, University of Central Florida, Orlando, Florida, USA; [b]School of Communication, Ohio State University, Columbus, Ohio, USA; [c]Department of Telecommunication, University of Florida, Gainesville, Florida, USA

ABSTRACT

New advancements in technology have made machines teachers, or technology-powered robots or AI that assist in the overall learning experience, a possibility. Though adoption rates are currently low, colleges and universities will likely incorporate some aspects of machine teachers (e.g., AI, robots) in their curriculums in the foreseeable future. However, little is known about how to create an effective machine teacher-based education. As an initial step, the present study examines whether an AI instructor's communication style would have an impact on students' perceptions about an AI instructor-based education. To test this inquiry, the study conducted an online experiment using a 2 (communication styles: functional vs. relational) x 2 (course topic: natural science vs. social science) between-subjects design. Primary results indicate that students develop more favorable perceptions about an AI instructor-based education when the AI instructor is relational rather than functional. This tendency is particularly strong when listening to a social science lecture. Further, social presence of an AI instructor functions as a mediator, which explains the reason why a relational AI instructor leads to more favorable perceptions about an AI instructor-based education is because of one's social presence of an AI instructor. Collectively, the study's findings indicate the importance of communication styles and social presence of an AI instructor.

Although robots have long been in the classroom (Cooper et al., 1999), recent years have witnessed increased attention to the use of robots and AI (artificial intelligence) for educational experiences. These technologies take on a variety of tasks, such as aiding in learning and providing feedback and instruction to students. In fact, an AI named Jill Watson, which was built based on IBM's Watson platform, was introduced in an online class and served as a "teaching assistant" for students to interact with (Georgia Tech, 2017). Overall, research notes positive effects of employing new technologies in student learning (Ahmad et al., 2016).

With the advancement of technology, the field of education is expected to experience some novel changes in the foreseeable future. In particular, human teachers might become more focused on serving as a supervisor that creates, designs, and selects machine-led delivery and content, assists with student progress, and provides pastoral support during the learning process (C. Edwards et al., 2018). Considering that much of communication is a scripted endeavor (Kellerman, 1992), lecture delivery in online education might be effectively and easily supplemented by machine agents. Although it might take some time for machine teachers to be fully adopted in educational contexts, the trend seems to be heading in this direction. As we prepare for this new era of education, it is vital to understand how to create effective and communicative machine teachers. However, given that research regarding machine teachers is in the nascent stage, there exists considerable uncertainty and a lack of information in this area. Naturally, this calls for research regarding this topic.

Research identifies several factors that contribute to the effective use of new technologies in educational contexts, such as perceived immediacy and credibility of robot teachers (C. Edwards et al., 2018). However, little is known about the communication or interaction styles of machine teachers. Technological affordances allow humans to design and create lecture content in advance and program the machine to deliver it. In this regard, the question is whether the way machines deliver a lecture to students (e.g., communication or interaction styles) would have any impact on student perceptions and learning experiences.

To start unpacking this important, new area of research, the present study investigates how a machine teacher's communication styles, when giving a lecture, influence students' perceptions about a machine teacher-based education. Further, to explore the underlying mechanism of why a machine teacher's communication style would matter, the present research examines this through the theoretical lens of social presence. Acknowledging the continuously increasing demand and popularity of online classes in higher education (Allen & Seaman, 2017), the present study examines this

CONTACT Jihyun Kim Jihyun.Kim@ucf.edu Nicholson School of Communication and Media, University of Central Florida, 500 W. Livingston Street, Orlando, FL 32801, USA

research inquiry with a disembodied machine teacher, particularly an AI instructor, that can be effectively incorporated into online education.

1. Literature review

1.1. Online education and communication styles of instructors

The educational experience is constantly transformed by use of the expeditious advancements of new technologies. Today, it is no longer a surprise to see a significant proportion of online classes in higher education. Statistics reports that more than 35% of college students enrolled in at least one online course in 2018 (National Center for Education Statistics, 2019). The popularity of online education is expected to continuously increase even after the COVID-19 pandemic, which required most educational institutions to incorporate some form of online learning in their course schedules.

To maximize the effectiveness of student learning in an online environment, much endeavor is being made. Kaufmann et al. (2016) explain that "the online classroom climate may be described as a perceived connection to, rapport for, or affinity with teacher and students within a mediated or online class" (p. 318) and highlight the importance of the online classroom climate. A positive classroom climate contributes to effective learning experiences and the role of the instructor is crucial in this process (Kaufmann et al., 2016). In particular, instructors' communication styles seem to play an important role in fostering positive learning experiences. For example, Dixson et al. (2017) found that instructors' nonverbal immediacy behaviors are closely related to student engagement in online classes. Collectively, the extant research highlights the importance of instructors' communication styles in online education.

The role of communication styles in instruction is examined from both rhetorical and relational perspectives. As Mottet et al. (2006) explain, rhetorical communication is task-oriented and content-focused (e.g., content relevance and clarity). In other words, this line of research seeks to answer what teacher communication strategies "get others to do what you want them to do?" (McCroskey & Richmond, 1996, p. 234). Relational communication, on the other hand, is concerned with the role communication plays in fostering an ongoing connection with others (Mottet et al., 2006). More specifically, this work examines student perceptions about the teacher's relational communication style (e.g., immediacy, rapport). The focus of this approach is to ask such questions as, "What role does teacher immediacy play in student motivation to learn?" Although there may be varying degrees, some teachers might focus on providing content in a straight-forward way while others might use the strategy of relationship building as part of fostering learning experiences. In this regard, the communication styles teachers have with students can be broadly understood as either functional or relational.

Research argues that teacher communication style influences affective, cognitive, and behavioral learning (Hosek & Houser, 2018). Students learn best when they perceive the instructor as competent, of good character, and caring (Finn & Ledbetter, 2014). And, they have positive learning experiences when the teacher uses appropriate self-disclosure (Song et al., 2019) and humor (Wanzer & Frymier, 1999). Their efficacy and behavioral learning are enhanced when the teacher fosters positive rapport (Frisby & Buckner, 2018) with students and responds to their efforts with confirmation that highlight them as "valuable, significant individuals" (Ellis, 2004, p. 2). Teachers' communication styles in higher education are especially important as these interactions affect students' self-perceptions, involvement, and achievement (González et al., 2018).

Acknowledging the importance of a teacher's communication style, now, the question is whether the teacher communication styles would still matter when the "teacher" is a "machine." A. Edwards and Edwards (2018) describe human-machine communication (HMC) in instructional environments as "when students or instructors use messages to interact with mobile devices (smartphones, tablets, laptops), virtual and augmented reality systems, AI pedagogical agents, and social robots" (p. 185). In this regard, it is important to start unpacking the idea of machine teachers.

1.2. Machine teachers

As technology continues to advance, the past few years have witnessed much incorporation of diverse technologies into education. Already, AI software and robots are employed as teachers' aides, tutors, and peer learning specialists in classrooms around the world (e.g., Vasagar, 2017). This trend naturally birthed the idea of machine teachers. The notion of machine teachers is generally understood as "a technology that plays a meaningful role during an interaction with humans in helping them engage in affective, cognitive, and behavioral learning through various ways" (Kim, Merrill Jr., Xu, et al., 2020).

Machine teachers can appear in diverse ways, such as embodied and disembodied forms (Kim, Merrill Jr., Xu, et al., 2020). Embodied agents are created with a physical instantiation or a physical body, and embodied machine teachers are used in diverse educational contexts. For example, telepresence robots at London's Saatchi gallery are employed to provide remote education sessions about the exhibited paintings and sculptures via digital channels (McDill, 2020). DragonBot is another example of an embodied machine teacher that tells stories to children as part of the learning process (Westlund, 2017). Additionally, Little Sophia is launched as a tutorial companion to inform children of basic programming and coding skills (Hanson Robotics, 2019).

Acknowledging the rise of embodied agents in education, scholars started investigating the effectiveness of embodied machine teachers compared to human teachers. C. Edwards et al. (2021) examined how students perceive a robot evaluator compared to a human evaluator for public speaking skills. Although students reported more positive evaluations and social perceptions (e.g., attraction, social presence) of a human evaluator than a robot evaluator, both evaluators received favorable responses that are above the midpoint of the evaluation scales. Along the same line, C. Edwards et al.

(2016) found that a social robot could be perceived as credible in a college classroom.

Unlike embodied machine teachers, disembodied machine teachers are based on software that conducts a conversation via auditory or textual methods without a physical instantiation. Currently, a few disembodied machine teachers are being used in educational settings. For example, Cognitive Tutor, one of the oldest programs used for pedagogical teaching, is used at over 2,000 schools around the country (Viadero, 2009). Duolingo, a second language learning software, also created a series of chatbots to help language learners practice the language (Wolhuter, 2019). Similarly, the AI-driven SnatchBot is used to execute repetitive administrative tasks such as answering students' questions regarding lesson plans, course modules, and assignment deadlines (Wolhuter, 2019).

From a scholarly standpoint, research started to explore student perceptions about AI-based devices in higher education. C. Edwards et al. (2019) examined the role of an AI instructor's voice on student perceptions. The study found that students that self-identified themselves as old evaluated the AI voice that sounds aged (old) as more credible and socially present than those that self-identified themselves as young. This finding implies the potential of customizing AI instructors that accommodate students with different characteristics and needs. In all, although the term "machine teachers" is relatively new, the idea of incorporating machine agents, whether embodied or disembodied, in educational settings has received continuous attention from both industry and academia.

To develop a foundational understanding of how students will perceive machine teachers, it is important to address this question from a theoretical framework that guides the way humans perceive machines. The Computers as Social Actors (CASA) paradigm, derived from The Media Equation (Reeves & Nass, 1996), is a theoretical perspective that focuses on social responses to communication technologies. Specifically, CASA states that when humans interact with computers, they will engage with the computer as if they were interacting with another human. That is, humans, unbeknownst to themselves, apply social scripts when interacting with computers and treat computers in a similar manner to how they would treat a human.

Since the inception of the CASA paradigm, various studies have used this perspective to better understand how individuals interact with machines, beyond computers. For example, research notes that people consider and respond to feedback received from a video game avatar as if it were from humans (Kim & Timmerman, 2018). Further, the mere presence of an animated computer icon leads to some positive effects that support social facilitation (Hall & Henningsen, 2008).

Interestingly, people often state that they would not interact with computers/machines and humans in the same manner, with a preference for humans (Reeves & Nass, 1996). Spence et al. (2014) deemed this preference as the "human-to-human interaction script" (p. 277). Central to the human-to-human interaction script are differences in expectations when interacting with another human or a machine. Confirming the core of the human-to-human interaction script, various research studies report empirical support for the argument (e.g., C. Edwards et al., 2016, 2019; Spence et al., 2014). Importantly, A. Edwards et al. (2019) revealed that after an actual interaction with a robot, people experience more favorable perceptions toward a robot interaction compared to their initial expectations. This finding implies that although people may initially possess different expectations between a human vs. machine interaction, once they are engaged in an actual interaction, they may perceive a human and machine agent in a similar manner.

In all, the present research argues that even if a teacher is a machine, students would perceive the machine teacher as if it were a human teacher. Thus, based on the literature that highlights the importance of teachers' communication styles (e.g., González et al., 2018; Song et al., 2019), the CASA paradigm (Reeves & Nass, 1996), and the human-to-human script (Spence et al., 2014), this study argues that a machine teacher's communication styles are vital in developing students' perceptions about the use of machine teachers in their learning. Considering the study's interest in the adoption of machine teachers in online education, a disembodied machine teacher, particularly the role of an AI instructor, is tested. Taken together, the study proposes the following hypothesis.

H1a-b: An AI instructor's communication styles (functional vs. relational) have significant effects on students' perceptions about an AI instructor-based education, such as (a) attitudes toward an AI-based education and (b) intentions to enroll in an AI-based education.

Another important question to consider in this realm is whether students prefer specific communication styles for certain subjects of study. For example, many subjects in the social sciences involve relational and communication components that might sometimes require subjective interpretations or understanding. However, natural sciences, such as math and biology often require students to memorize specific problems or equations, which typically have objective answers or approaches. In this regard, it appears to be important to understand whether the effect of a teacher's communication style would vary depending on the subject being taught. That is, considering the nature of the subjects, it is questionable whether a functional style might work better for a natural science course, while the relational style might work better for a social science course. Hughes (2009) found a positive correlation between students' understanding of concepts and a teacher's interactive, approachable styles. However, Norwood (1994) found that relational teaching is less effective than instrumental teaching (functional-based teaching) in a college-level mathematics course. Considering these somewhat inconclusive findings and the lack of supporting evidence, the study raises the following research question.

RQ1a-b: Does the effect of an AI instructor's communication styles vary by course topics on perceptions about an AI instructor-based education, such as (a) attitudes toward an AI-based education and (b) intentions to enroll in an AI-based education?

1.3. Social presence

As discussed earlier, the CASA paradigm argues that people treat technology as they would treat other humans (Reeves & Nass, 1996). Then, the question is why do people tend to apply the same social rules to both technology and humans? Although there might be more than one answer for this phenomenon, one strong and plausible explanation stems from the theoretical notion of social presence.

Over the last few decades, research documents multiple conceptualizations of social presence. Of them, K. Lee (2004b) defines social presence as "a psychological state in which virtual social actors are experienced as actual social actors in either sensory or non-sensory ways" (p. 37). That is, social presence is concerned with the experiences with other agents, whether with humans or technological agents manifesting humanness (e.g., artificial social actors).

Social presence is neither a simple nor a unidimensional concept (Biocca et al., 2003). The extant research identifies multiple aspects or dimensions of social presence, such as social presence as psychological involvement and social presence as copresence (Biocca et al., 2003; Kelly & Westerman, 2016). Social presence as psychological involvement is concerned with a deeply immersed feeling of another, such as salience or immediacy of the other (Biocca et al., 2003; Short et al., 1976). Social presence as copresence is mostly concerned with a feeling of being together with another entity in the same space. Fundamentally, it is a perception of being with the other in the same space although they are physically apart.

Social presence can be heightened by social factors (K. M. Lee & Nass, 2005), and this argument is well supported by empirical research findings in diverse contexts. For instance, research reports that sharing life stories (Kim & Yang, 2019) and positive feedback messages (Kim & Timmerman, 2018) tend to induce strong social presence. Similarly, Kim and Song (2016) find that communicating about personal and relational life stories, compared to professional life stories, fosters stronger social presence of the interaction partner. Overall, the extant body of literature documents how communication styles, particularly social or relational styles, foster social presence.

Research also highlights that social presence fosters positive mediated, virtual experiences (Biocca et al., 2003). Germain to the context of this study, the body of literature documents that social presence leads to effective learning experiences in an online environment (e.g., Akyol & Garrison, 2008; Kim et al., 2016; Strong et al., 2012). Confirming the literature, the positive role of social presence in online learning experiences is also well summarized in Richardson et al.'s (2017) systematic meta-analysis.

In all, the extant research shows that social factors, such as relational communication styles, enhance a feeling of social presence, and the heightened social presence leads to positive mediated, virtual experiences. This argument essentially points to the mediating role of social presence. In fact, a considerable body of empirical research documents the mediation effect of social presence in diverse contexts such as human-robot interaction (e.g., K. M. Lee et al., 2006), digital gameplay (e.g., Kim & Timmerman, 2018), social media (e.g., Kim & Song, 2016), social TV viewing (e.g., Kim, Merrill Jr., Collins, 2020; Kim et al., 2019, 2018; Kim, Yang, et al., 2020), radio listening (e.g., Kim & Yang, 2019), and online learning (e.g., Song et al., 2019).

Baron and Kenny (1986) argue that "mediators speak to how or why such effects occur" (p. 1176). In this regard, the present research predicts that the reason why communication styles of an AI instructor influence students' perceptions about an AI instructor-based education (H1a-b) is because of the social presence of an AI instructor. Taken altogether, the study proposes the following hypothesis. See Figure 1.

H2a-b: Social presence mediates the relationship between an AI instructor's communication styles (functional vs. relational) and perceptions about an AI instructor-based education, such as (a) attitudes toward an AI-based education and (b) intentions to enroll in an AI-based education.

2. Methods

The present study conducted an online experiment, employing a 2 (communication style: functional vs. relational) x 2 (course topic: natural science vs. social science) between-subjects design. To test the proposed hypotheses and research question, voice-based lecture clips were created for this study.

2.1. Participants

The recruitment occurred at a large, public University in an urban city in the southeastern U.S. Initially, a total of 278 individuals responded to this study. To filter out inattentive responses and to ensure the quality of the data, a series of data screening processes were performed. First, eight individuals indicated that they have taken this study previously; thus, they were removed. Second, an attention check was performed in the middle of the questionnaire to ensure that participants were paying attention to the questions. Two individuals failed the attention check and were eliminated from the data. Another attention check was performed to ensure that

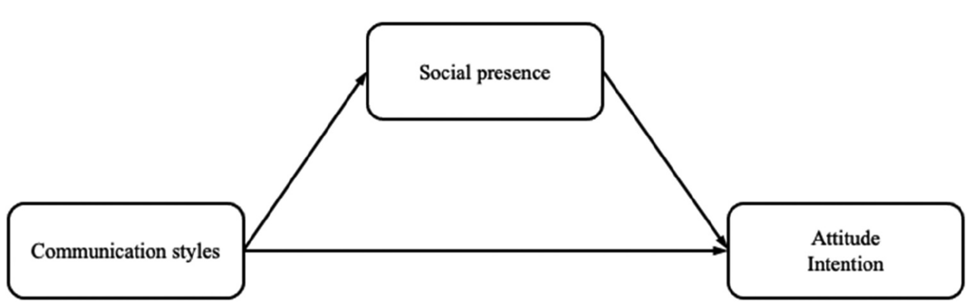

Figure 1. The mediation model.

participants paid attention to the lecture clip, which was the experimental stimulus. The study found that thirty-one individuals failed to identify the lecture they listened to; therefore, they were removed from the data.

After the data screening process, the final sample included 237 participants. The sample primarily consisted of females (n = 154: 65%), and the average age was 20.62 years (SD = 4.49). The majority of participants identified as White/Caucasian (n = 123: 51.9%), followed by Latino/a/x or Hispanic (n = 58: 24.5%), Black/African American (n = 29: 12.2%), and other racial and ethnic groups (n = 27: 11.4%). Participants were randomly assigned to one of four conditions: functional style in a natural science lecture (n = 64), functional style in a social science lecture (n = 54), relational style in a natural science lecture (n = 60) or relational style in a social science lecture (n = 59). Although random assignment was used, cell sizes were not balanced due to the series of data cleaning processes described above.

2.2. Procedure

Following the approval by a university's Institutional Review Board (IRB), initial recruitment was announced in several undergraduate courses. Interested individuals were invited to click on a link to the research participation website that was included in the recruitment message. Upon clicking the link, participants were asked to read and acknowledge the informed consent before proceeding to the research participation. Participants were also reminded that they would need a headset to participate in this research.

The study consisted of three sections. The first section included questions that assess participants' preexisting attitudes toward new technologies. The second section included a voice-based lecture and questions about the lecture. In this section, participants were told that they would listen to a lecture recorded by an AI instructor. Then, they were randomly assigned to one of the four lecture clips. In order to avoid a situation where participants click to the next page without listening to the lecture clip, a timer was set, which did not allow participants to go to the next page until the clip ended. Following the lecture, participants were asked to answer a series of questions regarding their perceptions about the lecture and an AI instructor. The last section included several demographic questions. Participation was voluntary, and all participants received course credit or extra credit. Confidentiality and anonymity were guaranteed.

2.3. Materials

Four voice-based lecture clips were created for this experiment. Each lecture consisted of three sections: 1) opening conversation before the lecture, 2) the course content, and 3) transitioning/closing conversation after the course content. The sections for the conversations before and after the main course content were manipulated to assess the effect of the communication styles (functional vs. relational). The section for the course content was manipulated to assess the effect of the course topic (natural science vs. social science).

Regarding the communication styles, the AI instructor shared different conversation topics with students. For the functional style condition, the conversation topic was about class-related matters. For example, the AI instructor gave a reminder of the upcoming exam and emphasized the importance of understanding basic concepts. For the relational style condition, the conversation topic was focused on relationship building. For example, the AI instructor asked the students how they are doing and whether they are enjoying their social life and highlighted the importance of relationship building in learning experiences.

For the course topic, two specific subject areas were selected. For natural science, a biology course was selected. The course content was focused on basic information about cells, which is typically taught in an introductory biology course. For social science, a communication course was selected. The course content was focused on three types of communication conflict, which is typically taught in an introductory communication course.

Based on the lecture script for each condition, the study developed voice-based lectures. A few steps were taken to create the lecture clips. First, the text-to-speech (TTS) software on OSX system "SayIt" was used to convert lecture scripts to audio clips. Then, several machine voices available in the software were assessed to identify the most suitable voice, which is not too machine-like or human-like. After comparing several options, a female voice "Samantha" was selected. To control for the confounding factors, the four audio clips were all edited to have a similar pitch, length, and rate (160 words per minute). Each clip was approximately 100-second long.

2.4. Measures

Before the stimulus lecture clip, attitudes toward new technologies (α = .75) were measured with three items adopted from C. I. Nass et al. (1995). Example items included: "How comfortable would you be with new technologies (e.g., robots, AI) taking routinized roles (e.g., accountants, auto mechanics, bank tellers)" and " … taking personal roles (e.g., colleagues, bosses)." Responses were obtained on a 6-point scale (1 = Very Uncomfortable, 6 = Very Comfortable).

After the stimulus, several measures regarding participants' perceptions about an AI instructor-based education were assessed. First, attitudes toward an AI-based education (α = .96) were measured with five items (e.g., "negative – positive," "harmful – beneficial") adopted from Davis (1993). Responses were obtained on a 7-point semantic differential scale.

Intentions to enroll in an AI-based education (α = .96) were measured with three items (e.g., If an AI-based online class is available … "I would consider taking the class" and "I intend to take the class"). Items were adopted from (Choi & Ji, 2015) and slightly modified for the study context. Responses for attitudes and intentions were obtained on a 7-point Likert-type scale (1 = Strongly Disagree, 7 = Strongly Agree).

Social presence as psychological involvement (α = .93) was measured with eight items (e.g., When listening to the AI's lecture, I felt like the AI was … "unresponsive – responsive," "unsociable – sociable," and "impersonal– personal"). Items were adopted from the extant literature (Lombard et al., 2009; Short et al., 1976). Responses were obtained on a 7-point semantic differential scale.

Social presence as copresence (α = .93) was assessed with four items (e.g., When I was hearing the AI's lecture, I felt like … "the AI was with me" and "the AI was interacting with me in the same space"). Items were adopted from K. M. Lee et al. (2006). Responses were obtained on a 7-point Likert-type scale (1 = Strongly Disagree, 7 = Strongly Agree). A complete questionnaire is available upon request to the corresponding author.

3. Results

Before hypothesis testing, a control variable was considered. Specifically, analyses were conducted while controlling for participants' preexisting attitudes toward new technologies. This decision was made because preexisting attitudes toward new technologies might have influenced participants' overall responses toward the lecture delivered by an AI instructor, regardless of the experimental condition. In fact, extant research reports that preexisting attitudes toward new technologies is related to perceptions about an AI instructor-based education (e.g., Kim, Merrill Jr., Xu, et al., 2020).

3.1. H1a-b and RQ1a-b: The effects of communication styles and course topic

A series of ANCOVA were conducted to test the proposed sets of hypotheses and research questions that examined the effects of an AI instructor's communication styles (H1a-b) and whether the effect of communication styles vary by the course topic (RQ1a-b). First, a test was conducted to examine H1a and RQ1a that were concerned with attitudes toward an AI-based education. Regarding H1a, the data indicated significant differences, $F(1, 232) = 4.80$, $p < .05$, $\eta_p^2 = .020$. Individuals in the relational style condition ($M = 3.35$, $SD = 1.52$) reported more favorable attitudes than those in the functional style condition ($M = 2.98$, $SD = 1.55$). With regard to RQ1a, there was no significant difference between the two course topics, $F(1, 232) = 0.38$, $p > .05$, $\eta_p^2 = .002$ [natural science ($M = 3.08$, $SD = 1.42$), social science ($M = 3.26$, $SD = 1.68$)]. Further, there was no significant interaction effect, $F(1, 232) = 0.50$, $p > .05$, $\eta_p^2 = .002$.

Although no significant interaction effect was detected, the pattern of the results indicated a potential simple effect. Thus, additional analyses were performed to closely assess the pattern of the results. In the natural science condition, no difference was found between the relational style condition ($M = 3.19$, $SD = 1.26$) and functional style condition ($M = 2.98$, $SD = 1.56$), $F(1, 232) = 1.15$, $p > .05$, $\eta_p^2 = .005$. However, in the social science condition, a significant difference was observed, $F(1, 232) = 4.02$, $p < .05$, $\eta_p^2 = .017$. Individuals in the relational style condition ($M = 3.52$, $SD = 1.75$) reported more favorable attitudes toward an AI-based education than those in the functional style condition ($M = 2.98$, $SD = 1.56$). This finding indicates that the communication styles matter when listening to a social science lecture.

Another ANCOVA test was conducted to examine H1b and RQ1b regarding intentions to enroll in an AI-based education. For H1b, although the p-value was greater than the conventional level (.05), the data indicated a particular pattern of differences, $F(1, 232) = 3.03$, $p = .083$, $\eta_p^2 = .013$. Individuals in the relational style condition ($M = 3.03$, $SD = 1.74$) reported stronger intentions than those in the functional style condition ($M = 2.71$, $SD = 1.80$). Regarding RQ1b, there was no significant difference between the two conditions, $F(1, 232) = 0.34$, $p > .05$, $\eta p^2 = .001$ [natural science ($M = 2.78$, $SD = 1.69$), social science ($M = 2.97$, $SD = 1.85$)]. However, the data found a significant interaction effect, $F(1, 232) = 5.90$, $p < .05$, $\eta_p^2 = .025$.

In order to better understand the significant interaction effect, a simple test was conducted to further examine the finding. In the natural science condition, no difference was found between the relational style ($M = 2.67$, $SD = 1.53$) and functional style ($M = 2.89$, $SD = 1.84$), $F(1, 232) = 0.25$, $p > .05$, $\eta_p^2 = .001$. However, in the social science condition, a significant difference was observed, $F(1, 232) = 8.31$, $p < .01$, $\eta_p^2 = .035$. Individuals in the relational style condition ($M = 3.40$, $SD = 1.87$) reported stronger intentions to enroll in an AI-based education than those in the functional style condition ($M = 2.51$, $SD = 1.73$). This finding indicates that the communication styles matter when listening to a social science lecture. See Table 1.

3.2. H2a-b: The mediating role of social presence

H2a-b predicted the mediating role of social presence between the AI instructor's communication styles and perceptions about the AI-based education: attitudes toward the AI-based education (H2a) and intentions to enroll in the AI-based education (H2b). As noted earlier, social presence is not a unidimensional concept (Biocca et al., 2003). Acknowledging the strong predictive validity of multidimensional aspects of social presence in educational contexts (Kim et al., 2016), the study examines both social presence as psychological involvement and social presence as copresence (Biocca et al., 2003; Kelly & Westerman, 2016). Thus, double mediators were used in the analyses.

Analyses were conducted using PROCESS (model #4) (Hayes, 2017). This method uses a bootstrapping approach, and the procedure was based on 5000 bootstrap samples. The results were interpreted based on the 95% Confidence Interval (CI). Communication style was dummy coded (0 = functional style, 1 = relational style).

Regarding H2a, the results indicated that both aspects of social presence collectively mediated the relationship between the AI instructor's style and attitudes toward the AI-based education (indirect effect = .70, Boot SE = .13; CI = [0.46, 0.96]). In order to examine the mediation effect of each aspect of social presence, the results were further assessed. For social presence as psychological involvement, there was a significant mediation effect (indirect effect = .63, Boot SE = .12; CI = [0.41, 0.88]). Participants in the relational condition, compared to the functional condition, reported stronger social presence as psychological involvement (a = 1.12), which led to

Table 1. The effects of communication styles and course topics (H1a-b & RQ1a-b).

IV	DV	Condition	M (SD)	F	ηp^2
Communication Style	Attitude	Relational	3.35 (1.52)	4.80*	.020
		Functional	2.98 (1.55)		
	Intention	Relational	3.03 (1.74)	3.03	.013
		Functional	2.71 (1.80)		
Course Topic	Attitude	Natural science	3.08 (1.42)	0.38	.002
		Social science	3.26 (1.68)		
	Intention	Natural science	2.78 (1.69)	0.34	.001
		Social science	2.97 (1.85)		

* $p < .05$. M: Mean; SD: Standard deviation
Interaction effect on attitude: $F(1, 232) = .50$, $\eta_p^2 = .002$
Interaction effect on intention: $F(1, 232) = 5.90^*$, $\eta_p^2 = .025$

more favorable attitudes (b = .56). For social presence as copresence, there was a significant mediation effect (indirect effect = .07, Boot SE = .04; CI = [0.01, 0.16]). Participants in the relational condition, compared to the functional condition, reported stronger social presence as copresence (a = .42), which led to more favorable attitudes (b = .16). In all, the results indicate that both aspects of social presence function as mediators, collectively as well as individually.

With regard to H2b, the results indicated that both aspects of social presence collectively mediated the relationship between the AI instructor's communication style and intentions to enroll in the AI-based education (indirect effect = .62, Boot SE = .14; CI = [0.35, 0.90]). In order to examine the mediation effect of each aspect of social presence, the results were further evaluated. For social presence as psychological involvement, there was a significant mediation effect (indirect effect = 0.48, Boot SE = .12; CI = [0.27, 0.73]). Participants in the relational condition, compared to the functional condition, reported stronger social presence as psychological involvement (a = 1.12), which led to stronger intention (b = .56). For social presence as copresence, there was a significant mediation effect (indirect effect = .13, Boot SE = .07; CI = [0.02, 0.28]). Participants in the relational condition, compared to the functional condition, reported stronger social presence as copresence (a = .43), which led to stronger intentions (b = .32). In all, the results indicate that both aspects of social presence function as mediators, collectively as well as individually. See Table 2.

Table 2. The mediation effects of social presence (H2a-b).

DV	Mediator	B (SE)	95% CI LLCI	95% CI ULCI
Attitude	Collectively	.70 (.13)	.46	.96
	Psychological involvement	.63 (.12)	.41	.88
	Copresence	.07 (.04)	.01	.16
Intention	Collectively	.62 (.14)	.35	.90
	Psychological involvement	.48 (.12)	.27	.73
	Copresence	.13 (.07)	.02	.28

ULCI: upper-level confidence interval, LLCI: lower-level confidence interval. B: unstandardized coefficient. SE: standard error.
Mediator: (a) collectively: social presence both as psychological involvement and copresence; (b) social presence as psychological involvement; (c) social presence as copresence

4. Discussion

The present research examined the roles of an AI instructor's communication styles and social presence. The primary findings indicate that a relational AI instructor has more positive effects on students' perceptions about an AI instructor-based education than a functional AI instructor. In particular, this tendency appears to be strong when listening to a lecture from a social science course. Further, the study finds that the reason why an AI instructor's communication styles matter is because of the social presence of the AI instructor.

4.1. Primary findings

The present research reveals meaningful findings. First, the study finds that students develop more positive attitudes when the AI instructor is presented with a relational communication style than with a functional communication style. This finding is consistent with previous research that indicates students prefer relational and friendly teachers (Potter & Emanuel, 1990), and teachers are expected to be good communicators, emotionally intelligent, and creative (B. I. Edwards & Cheok, 2018). Although marginally significant, the current study also finds that students develop stronger intentions to enroll in an AI-based education when the AI instructor uses a relational style than a functional style. Given that a teacher's communication style is indicative of many student outcomes, including achievement, involvement, and perceptions (González et al., 2018), this finding is meaningful.

Further, the study also finds that the effect of an AI instructor's communication styles particularly matter in a lecture from a social science course. That is, when listening to a lecture from a social science course, students report more favorable perceptions about an AI instructor-based education when the AI instructor uses a relational style than a functional style. In social sciences, students are often learning about human-related materials such as relationships, perceptions, and behaviors, especially in the communication discipline. Thus, it is likely that students prefer a relational teacher who goes beyond the simple functional-based teaching of the material and who builds a rapport with students. Overall, these findings of an AI instructor's communication styles support the CASA paradigm, as students tend to mindlessly treat the AI instructor as if they were human teachers.

Moreover, this study highlights the mediating role of social presence. Specifically, the study finds that the reason why a relational style, compared to a functional style, leads to more positive perceptions about an AI instructor-based education is due to the social presence of the AI instructor. That is, a relational style, compared to a functional style, leads to stronger social presence of the AI instructor, which fosters more favorable perceptions about an AI instructor-based education. In fact, the mediating role of social presence is well supported by extant research. From a theoretical standpoint, the mediating role of social presence provides a fundamental understanding of the CASA paradigm. That is, the reason why people treat technology as social beings (Reeves & Nass, 1996) is because of the social presence people feel toward technology while interacting with it. Supporting K. Lee's (2004a) argument that social presence lies at the heart of the CASA paradigm, the finding of the present research implies that social presence is a key underlying mechanism in human-machine communication.

4.2. Implications and contributions

The findings of the present study make meaningful implications and contributions. First, the study's findings are meaningful for advancing social presence research by highlighting the importance of social factors for fostering social presence when interacting with machines. In fact, extant research suggested a few theory-driven causal factors for social presence, or presence (for a broader notion of presence, see K. Lee, 2004b), such as technology-related factors, individual factors, and social factors (K. M. Lee & Nass, 2005; Lombard & Ditton, 1997). In early research, technology-related factors and individual factors have received much attention (Lombard & Ditton, 1997). However, acknowledging Biocca et al.'s (2003) argument that social presence is a phenomenological state that not only varies with media technologies but also with the awareness of other social actors, the content of the messages, and communication contexts, it is evident that social factors are also vital in inducing social presence. Although it might be true that social presence can be maximized through advanced technological features (e.g., vividness, size), the present research implies that social cues embedded in the way machines interact with humans can also play a vital role. In fact, this is in line with K. M. Lee and Nass (2005) argument that social factors foster social presence.

Further, the study highlights the importance of the multiple dimensions of social presence. As argued in the extant research (e.g., Biocca et al., 2003), there exist multiple aspects or dimensions of social presence. Although this argument has been around for decades, most of the studies appear to examine a single dimension of the notion. Acknowledging the strong predictability of multiple aspects of social presence in an educational context (Kim et al., 2016), the present research tested two aspects of social presence that are identified in the literature, social presence as psychological involvement and social presence as copresence (Biocca et al., 2003; Kelly & Westerman, 2016). By testing both aspects together as well as individually, the present study supports the importance of multidimensional aspects of social presence.

Next, the current study provides important contributions to HMC. In particular, the findings suggest that an AI instructor's communication styles matter. The present study observed that students develop different perceptions about the relational and functional AI instructors, with more favorable attitudes toward the relational AI instructor. From a scholarly standpoint, it is important to test whether these differences in communication styles will hold for machines in other contexts. For example, would an individual prefer a healthcare robot that is relational or functional? Depending on the situation, an individual may prefer a relational healthcare robot if they are seeking a robot therapist, but they may instead prefer a functional healthcare robot when having an annual checkup at the hospital. Accounting for these potential differences in communication styles for future machines in other areas will be necessary.

Moreover, the conclusions from the present study also point to important implications for instructional communication theory and practice. In particular, the study contributes to the understanding of how to create an effective AI instructor in online education. To date, considerable research has been published about the influence instructional or communication styles have on student perceptions and learning in online environments (e.g., Frisby et al., 2013; Kaufmann et al., 2016; Kim et al., 2016). However, little is known about the role of teacher communication styles in higher education when the "teacher" is a "machine." A. Edwards and Edwards (2018) describe HMC in instructional environments as "when students or instructors use messages to interact with mobile devices (smartphones, tablets, laptops), virtual and augmented reality systems, AI pedagogical agents, and social robots" (p. 185). Machine teachers are used in several ways in teaching and learning; however, relatively few studies are published examining its utility in fostering learning, either directly or indirectly (Sharkey, 2016). A few studies do examine, for example, perceptions of teacher credibility and learning when the teacher is a robot (Edwards et al., 2016) and student perceptions of AI as teaching assistants (Kim, Merrill Jr., Xu, et al., 2020). However, more research is warranted that explores HMC and learning, particularly in online education. In this regard, the study contributes to HMC in instructional communication.

The study's findings also provide a critical foundation for the use of AI instructors, more broadly machine teachers, in higher education. Since attitudes are a key predictor of student motivation to engage and learn, creating and programming machine teachers in specific ways seem critical to teaching and learning success. Also, when students perceive the machine teacher as exhibiting characteristics of a positive relational communication style, they are more likely to register for another machine teacher-based course in the future. Due to the COVID-19 pandemic, the need to capitalize on technology affordances such as AI and social robots in higher education has become increasingly transparent. It seems plausible that, if these machines can generate learning via effective communication styles, then they could be utilized effectively in instruction when health and safety may prohibit face-to-face interaction.

Further, to maximize the effectiveness of an AI instructor in online education, it is important to ensure that human instructors feel comfortable with incorporating the technology into their curriculum. Research notes that when instructors appear uncomfortable employing a particular pedagogy, students develop negative perceptions toward it (Liu et al., 2016). Thus, it is crucial to develop a training program for instructors, such as workshops and webinars, which teach them how to incorporate the technology and how to educate students to see the value of an AI instructor in learning. Also, Kim, Merrill Jr., Xu, et al. (2020) argue that perceived usefulness of an AI teaching assistant is a key to establishing a positive attitude, which eventually leads to an intention to enroll in AI-based education. Although the primary role of an AI teaching assistant and an AI instructor might be somewhat different, a similar, if not the same, rule might be applied. In this regard, it is important to promote the usefulness of an AI instructor by targeting both instructors and students to maximize the benefits of employing an AI instructor.

Finally, the present research also provides implications for practice. In particular, the findings suggest that educational technology developers should ensure that the technology incorporates relational styles in creating and delivering lectures to the users. Although it may seem trivial, the finding indicates that a technology's communication style significantly affects its users, which may ultimately lead to adoption of the technology by the masses. In fact, this implication can be applied to any type of machine that is designed for human interaction. The study's finding implies that social cues, although subtle, can facilitate effective human-machine communication. In this regard, computer scientists and engineers are encouraged to consider this implication when designing new machine agents.

4.3. Limitations and future research directions

Although the present study revealed interesting findings, the pattern of the results needs to be interpreted cautiously considering some of the limitations identified in this study. First, the present study examined one particular topic within a course for each condition. Although biology and communication are good examples that represent the natural science and social science disciplines respectively, there might be some variations across different subject matters within biology and communication courses or in other areas of study within the natural and social science disciplines. To have a better understanding of this research inquiry, future researchers are encouraged to replicate this study in other subjects with different content areas.

Second, the current study only looked at differences between functional and relational communication styles. However, teachers are likely to have some degree of both styles. Also, some disciplines may appreciate both relational and functional communication styles. Considering that teachers need to learn a variety of methods and styles related to effective teaching (Vaughn & Baker, 2001), future research should examine varying degrees of functional and relational styles in diverse course subjects.

Next, another limitation of this research is related to the voice of the AI instructor. Voice is an important component in human-computer/machine communication (C. Nass & Lee, 2001). Depending on the types of voices, students might develop different perceptions or credibility of the AI instructor. Due to the scope of the study, the present investigation only used a female-presenting voice. Research shows that students often rated female teachers higher in interpersonal characteristics and aspects than male teachers (Bennett, 1982). That is, female teachers received higher ratings of warmth and charisma than male teachers. Female teachers are also viewed more positively than male teachers (Wood, 2012). Thus, future research should investigate differences among male- and female-voiced AI instructors and how this may affect a student's perceptions of an AI instructor-based education. Also, it would be worth studying how varying degrees of mechanical voices in AI instructors (e.g., more machine-like vs. more human-like) influence student perceptions. In this regard, the study calls for more research in this realm.

Lastly, the study acknowledges that it was a cross-sectional study, which might be limited to explaining the study's findings to some degree. As the extant research (e.g., Spence et al., 2014) indicates, people would be more likely to apply the human-to-human script in their initial interactions. However, considering that a relationship is not a one-time experience, the study's findings might be limited in that regard. Thus, future researchers are encouraged to employ a longitudinal approach. As Fox and Gambino (2021) suggested, it would be worth investigating the human-machine relationship through modifications or extensions of interpersonal theories by examining intervening variables that might explain the unique nature of relationships with machine agents. Particularly, it would be meaningful to investigate whether students would develop perceived relationships with an AI instructor. While the extant research indicates the possibility of humans developing similar levels of interpersonal outcomes with machines (Edwards et al., 2019), another research finds that relationship formation with a machine agent decreases over time (Croes & Antheunis, 2021). Considering that the nature of a student-instructor relationship is somewhat different from a typical interpersonal relationship (e.g., friendship, romantic relationship), it is worth investigating how the relationship progresses between a student and AI instructor.

5. Conclusion

The present study sought to better understand how an AI instructor's communication style influences a student's perceptions of an AI instructor-based education, and why communication styles matter. The primary results indicated that students develop more favorable perceptions about an AI instructor-based education when the AI instructor is relational rather than functional. This tendency is particularly strong when listening to a social science lecture. Further, the present study reveals the mediating role of social presence, which explains the reason why a relational AI instructor leads to favorable perceptions among students is because of the perceived social presence of the AI instructor. Though more research is needed to better understand the nuances of communication styles among AI instructors, the present research provides an important and foundational understanding of the importance of AI instructors' communication styles. Further, the present study provides a meaningful foundation for understanding the idea of machine teachers in general, beyond AI instructors.

References

Ahmad, M. I., Mubin, O., & Orlando, J. (2016, October). *Understanding behaviours and roles for social and adaptive robots in education: Teacher's perspective*. Proceedings of the fourth international conference on human agent interaction (pp. 297–304). https://doi.org/10.1145/2974804.2974829

Akyol, Z., & Garrison, D. R. (2008). The development of a community of inquiry over time in an online course: Understanding the progression and integration of social, cognitive and teaching presence. *Journal of Asynchronous Learning Networks*, *12*(3–4), 3–22. https://doi.org/10.24059/olj.v12i3.72

Allen, E., & Seaman, J. (2017, May). *Digital learning compass: Distance education enrollment report 2017*. Babson survey research group. https://onlinelearningsurvey.com/reports/digtiallearningcompassenrollment2017.pdf

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Bennett, S. K. (1982). Student perceptions of and expectations for male and female instructors: Evidence relating to the question of gender bias in teaching evaluation. *Journal of Educational Psychology*, *74*(2), 170–179. https://doi.org/10.1037/0022-0663.74.2.170

Biocca, F., Harms, C., & Burgoon, J. K. (2003). Toward a more robust theory and measure of social presence: Review and suggested criteria. *Presence: Teleoperators & Virtual Environments*, *12*(5), 456–480. https://doi.org/10.1162/105474603322761270

Choi, J. K., & Ji, Y. G. (2015). Investigating the importance of trust on adopting an autonomous vehicle. *International Journal of Human-Computer Interaction*, *31*(10), 692–702. https://doi.org/10.1080/10447318.2015.1070549

Cooper, M., Keating, D., Harwin, W., & Dautenhahn, K. (1999). Robots in the classroom-tools for accessible education. *Assistive Technology on the Threshold of the New Millennium*, *6*, 448.

Croes, E. A., & Antheunis, M. L. (2021). Can we be friends with Mitsuku? A longitudinal study on the process of relationship formation between humans and a social chatbot. *Journal of Social and Personal Relationships*, *38*(1), 279–300. https://doi.org/10.1177/0265407520959463

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. https://doi.org/10.1006/imms.1993.1022

Dixson, M. D., Greenwell, M. R., Rogers-Stacy, C., Weister, T., & Lauer, S. (2017). Nonverbal immediacy behaviors and online student engagement: Bringing past instructional research into the present virtual classroom. *Communication Education*, *66*(1), 37–53. https://doi.org/10.1080/03634523.2016.1209222

Edwards, A., & Edwards, C. (2018). Human-machine communication in the classroom. In M. L. Houser & A. M. Hosek (Eds.), *Handbook of instructional communication: Rhetorical and relational perspectives* (2nd ed., pp. 184–194). Routledge.

Edwards, A., Edwards, C., Spence, P. R., Harris, C., & Gambino, A. (2016). Communicating with a robots in the classroom: Differences in students' perceptions of credibility and learning between "teacher as robot" and "robot as teacher". *Computers in Human Behavior*, *65*, 627–634. https://doi.org/10.1016/j.chb.2016.06.005

Edwards, A., Edwards, C., Westerman, D., & Spence, P. R. (2019). Initial expectations, interactions, and beyond with social robots. *Computers in Human Behavior*, *90*, 308–314. https://doi.org/10.1016/j.chb.2018.08.042

Edwards, B. I., & Cheok, A. D. (2018). Why not robot teachers: Artificial intelligence for addressing teacher shortage. *Applied Artificial Intelligence*, *32*(4), 345–360. https://doi.org/10.1080/08839514.2018.1464286

Edwards, C., Edwards, A., Albrehi, F., & Spence, P. (2021). Interpersonal impressions of a social robot versus human in the context of performance evaluations. *Communication Education*, *70*(2), 165–182. https://doi.org/10.1080/03634523.2020.1802495

Edwards, C., Edwards, A., Spence, P., & Lin, X. (2018). I, teacher: Using artificial intelligence and social robots in communication and instruction. *Communication Education*, *67*(4), 473–480. https://doi.org/10.1080/03634523.2018.1502459

Edwards, C., Edwards, A., Spence, P. R., & Westerman, D. (2016). Initial interaction expectations with robots: Testing the human-to-human interaction script. *Communication Studies*, *67*(2), 227–238. https://doi.org/10.1080/10510974.2015.1121899

Edwards, C., Edwards, A., Stoll, B., Lin, X., & Massey, N. (2019). Evaluations of an artificial intelligence instructor's voice: Social Identity Theory in human-robot interactions. *Computers in Human Behavior*, *90*, 357–362. https://doi.org/10.1016/j.chb.2018.08.027

Ellis, K. (2004). The impact of perceived teacher confirmation on receiver apprehension, motivation, and learning. *Communication Education*, *53*(1), 1–20. https://doi.org/10.1080/0363452032000135742

Finn, A. N., & Ledbetter, A. M. (2014). Teacher verbal aggressiveness and credibility mediate the relationship between teacher technology policies and perceived student learning. *Communication Education*, *63*(3), 210–234. https://doi.org/10.1080/03634523.2014.919009

Fox, J., & Gambino, A. (2021). Relationship development with humanoid social robots: Applying interpersonal theories to human/robot interaction. *Cyberpsychology, Behavior, and Social Networking*. https://doi.org/10.1089/cyber.2020.0181

Frisby, B. N., & Buckner, M. M. (2018). Rapport in the instructional context. In M. L. Houser & A. M. Hosek (Eds.), *Handbook of instructional communication: Rhetorical and relational perspectives* (2nd ed., pp. 126–137). Routledge.

Frisby, B. N., Limperos, A. M., Record, R. A., Downs, E. P., & Kercsmar, S. E. (2013). Students' perceptions of social presence: Rhetorical and relational goals across three mediated instructional designs. *Journal of Online Learning and Teaching*, *9*(4), 468–480.

Georgia Tech. (2017, December 14). *Jill Watson*. https://www.cc.gatech.edu/holiday/jill-watson

González, A., Conde, Á., Díaz, P., García, M., & Ricoy, C. (2018). Instructors' teaching styles: Relation with competences, self-efficacy, and commitment in pre-service teachers. *Higher Education*, *75*(4), 625–642. https://doi.org/10.1007/s10734-017-0160-y

Hall, B., & Henningsen, D. D. (2008). Social facilitation and human–computer interaction. *Computers in Human Behavior*, *24*(6), 2965–2971. https://doi.org/10.1016/j.chb.2008.05.003

Hanson Robotics. (2019, January 30). *Hanson robotics announces "Little Sophia", new educational STEM companion for kids 7 to 13*. GlobeNewswire. https://www.globenewswire.com/news-release/2019/01/30/1707660/0/en/Hanson-Robotics-Announces-Little-Sophia-New-Educational-STEM-Companion-For-Kids-7-to-13.html

Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (2nd ed.). The Guilford Press.

Hosek, A. M., & Houser, M. L. (2018). Introduction to instructional communication methodological approaches. In M. L. Houser & A. M. Hosek (Eds.), *Handbook of instructional communication: Rhetorical and relational perspectives* (2nd ed., pp. 207–208). Routledge.

Hughes, G. B. (2009). Students' perceptions of teaching styles in mathematics learning environments. *Mathematics Teaching-Research Journal Online*, *3*(2), 1–12.

Kaufmann, R., Sellnow, D. D., & Frisby, B. N. (2016). The development and validation of the online learning climate scale (OLCS). *Communication Education*, *65*(3), 307–321. https://doi.org/10.1080/03634523.2015.1101778

Kellerman, K. L. (1992). Communication: Inherently strategic and primarily automatic. *Communication Monographs*, *59*(3), 288–300. https://doi.org/10.1080=03637759209376270

Kelly, S. E., & Westerman, D. K. (2016). New technologies and distributed learning systems. In P. L. Witt (Ed.), *Handbook of communication and learning, 16: Communication and learning* (pp. 455-480). De Gruyter.

Kim, J., Merrill Jr., K., & Collins, C. (2020). Touchdown together: Social TV viewing and social presence in a physical co-viewing context. *The Social Science Journal*, 1–15. https://doi.org/10.1080/03623319.2020.1833149

Kim, J., Merrill, Jr., K., Xu, K., & Sellnow, D. D. (2020). My teacher is a machine: Understanding students' perceptions of AI teaching assistants in online education. *International Journal of Human–Computer Interaction*, *36*(20), 1902–1911. https://doi.org/10.1080/10447318.2020.1801227

Kim, J., Merrill Jr., K., & Yang, H. (2019). Why we make the choices we do: Social tv viewing experiences and the mediating role of social presence. *Telematics and Informatics*, *45*, 101281. https://doi.org/10.1016/j.tele.2019.101281

Kim, J., & Song, H. (2016). Celebrity's self-disclosure on Twitter and parasocial relationships: A mediating role of social presence. *Computers in Human Behavior*, *62*, 570–577. https://doi.org/10.1016/j.chb.2016.03.083

Kim, J., Song, H., & Lee, S. (2018). Individual differences in social TV viewing experiences: A mediating and moderating role of social presence. *Mass Communication and Society*, *21*(1), 50–70. https://doi.org/10.1080/15205436.2017.1350715

Kim, J., Song, H., & Luo, W. (2016). Broadening the understanding of social presence: Implications and contributions to the mediated communication and online education. *Computers in Human Behavior*, *65*, 672–679. https://doi.org/10.1016/j.chb.2016.07.009

Kim, J., & Timmerman, C. E. (2018). Effects of supportive feedback messages on exergame experiences. *Journal of Media Psychology*, *30*(1), 29–40. https://doi.org/10.1027/1864-1105/a000175

Kim, J., & Yang, H. (2019). How does a radio host's testimonial influence media experiences? The indirect effect of social presence. *Journal of Radio & Audio Media*, *26*(2), 336–350. https://doi.org/10.1080/19376529.2018.1509217

Kim, J., Yang, H., & Kim, J. (2020). Being social during the big dance: Social presence and social TV viewing for March Madness in public and private platforms. *The Social Science Journal*, 1–13. https://doi.org/10.1016/j.soscij.2019.04.004

Lee, K. (2004a). Why presence occurs: Evolutionary psychology, media equation, and presence. *Presence: Teleoperators and Virtual Environments*, *13*(4), 494–505. https://doi.org/10.1162/1054746041944830

Lee, K. (2004b). Presence, explicated. *Communication Theory*, *14*(1), 27–50. https://doi.org/10.1111/j.1468-2885.2004.tb00302.x

Lee, K. M., & Nass, C. (2005). Social-psychological origins of feelings of presence: Creating social presence with machine-generated voices. *Media Psychology*, *7*(1), 31–45. https://doi.org/10.1207/S1532785XMEP0701_2

Lee, K. M., Peng, W., Jin, S.-A., & Yan, C. (2006). Can robots manifest personality?: An empirical test of personality recognition, social responses, and social presence in human–robot interaction. *Journal of Communication*, *56*(4), 754–772. https://doi.org/10.1111/j.1460-2466.2006.00318.x

Liu, M., Navarrete, C. C., Scordino, R., Kang, J., Ko, Y., & Lim, M. (2016). Examining teachers' use of iPads: Comfort level, perception, and use. *Journal of Research on Technology in Education*, *48*(3), 159–180. https://doi.org/10.1080/15391523.2016.1175853

Lombard, M., & Ditton, T. (1997). At the heart of it all: The concept of presence. *Journal of Computer-Mediated Communication*, *3*(2). https://doi.org/10.1111/j.1083-6101.1997.tb00072.x

Lombard, M., Ditton, T. B., & Weinstein, L. (2009, November). *Measuring presence: The temple presence inventory*. Proceedings of the International Society for Presence Research Annual Conference, Los Angeles, CA.

McCroskey, J. C., & Richmond, V. P. (1996). Human communication theory and research: Traditions and models. In M. B. Salwen & D. W. Stacks (Eds.), *An integrated approach to communication theory and research* (pp. 233–242). Lawrence Erlbaum.

McDill, S. (2020, October 29). *Robots give private view of major pop art show*. Reuters. https://www.reuters.com/article/us-health-coronavirus-art-robots/robots-get-private-view-of-major-pop-art-show-idUSKBN27E1ZZ

Mottet, T. P., Richmond, V. P., & McCroskey, J. C. (2006). *Handbook of instructional communication: Rhetorical and relational perspectives*. Pearson.

Nass, C., & Lee, K. M. (2001). Does computer-synthesized speech manifest personality? Experimental tests of recognition, similarity-attraction, and consistency-attraction. *Journal of Experimental Psychology: Applied*, *7*(3), 171. https://doi.org/10.1037/1076-898X.7.3.171

Nass, C. I., Lombard, M., Henriksen, L., & Steuer, J. (1995). Anthropocentrism and computers. *Behaviour & Information Technology*, *14*(4), 229–238. https://doi.org/10.1080/01449299508914636

National Center for Education Statistics. (2019). *Fast facts: Distance learning*. https://nces.ed.gov/fastfacts/display.asp?id=80

Norwood, K. S. (1994). The effect of instructional approach on mathematics anxiety and achievement. *School Science and Mathematics*, *94* (5), 248–254. https://doi.org/10.1111/j.1949-8594.1994.tb15665.x

Potter, W. J., & Emanuel, R. (1990). Students' preferences for communication styles and their relationship to achievement. *Communication Education*, *39* (3), 234–249. https://doi.org/10.1080/03634529009378805

Reeves, B., & Nass, C. I. (1996). *The media equation: How people treat computers, television, and new media like real people and places*. Cambridge University Press.

Richardson, J. C., Maeda, Y., Lv, J., & Caskurlu, S. (2017). Social presence in relation to students' satisfaction and learning in the online environment: A meta-analysis. *Computers in Human Behavior*, *71*, 402–417. https://doi.org/10.1016/j.chb.2017.02.001

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

Short, J., Williams, E., & Christie, B. (1976). *The social psychology of telecommunications*. John Wiley & Sons.

Song, H., Kim, J., & Park, N. (2019). I know my professor: Teacher self-disclosure in online education and a mediating role of social presence. *International Journal of Human–Computer Interaction*, *35* (6), 448–455. https://doi.org/10.1080/10447318.2018.1455126

Spence, P. R., Westerman, D., Edwards, C., & Edwards, A. (2014). Welcoming our robot overlords: Initial expectations about interaction with a robot. *Communication Research Reports*, *31*(3), 272–280. https://doi.org/10.1080/08824096.2014.924337

Strong, R., Irby, T. L., Wynn, J. T., & McClure, M. M. (2012). Investigating students' satisfaction with eLearning courses: The effect of learning environment and social presence. *Journal of Agricultural Education*, *53*(3), 98–110. https://doi.org/10.5032/jae.2012.03098

Vasagar, J. (2017, July 13). How robots are teaching Singapore's kids. *Financial Times*. https://www.ft.com/content/f3cbfada-668e-11e7-8526-7b38dcaef614

Vaughn, L., & Baker, R. (2001). Teaching in the medical setting: Balancing teaching styles, learning styles and teaching methods. *Medical Teacher*, *23*(6), 610–612. https://doi.org/10.1080/01421590120091000

Viadero, D. (2009, December 22). Scholars test emotion– Sensitive tutoring software. *EducationWeek*. https://www.edweek.org/policy-politics/scholars-test-emotion-sensitive-tutoring-software/2009/12

Wanzer, M. B., & Frymier, A. B. (1999). The relationship between student perceptions of instructor humor and students' reports of learning. *Communication Education*, *48*(1), 48–62. https://doi.org/10.1080/03634529909379152

Westlund, J. M. K. (2017, August 17). *Understanding children's relationships with social robots*. International Society for Presence Research. https://ispr.info/2017/08/17/understanding-childrens-relationships-with-social-robots/

Wolhuter, S. (2019, July 26). *AI in education: How chatbots are transforming learning*. WeAreBrain. https://www.wearebrain.com/blog/ai-data-science/top-5-chatbots-in-education/

Wood, T. D. (2012). Teacher perceptions of gender-based differences among elementary school teachers. *International Electronic Journal of Elementary Education*, *4*(2), 317–345.

About the Authors

Jihyun Kim is an Associate Professor in the Nicholson School of Communication and Media at the University of Central Florida. Her primarily research focuses on the effects and implications of new media/communication technologies for meaningful outcomes (e.g., education, health). Her research also examines human-machine communication in diverse contexts.

Kelly Merrill Jr. is a Ph.D. student at The Ohio State University. His primary research interests are at the intersection of communication technology and health communication. In particular, his research investigates the use of communication technologies for health-related outcomes.

Kun Xu is an Assistant Professor at the Department of Telecommunication, University of Florida. His research focuses on the intersection of human-computer interaction and media psychology. He investigates how people perceive, evaluate, and respond to robotic technologies such as social robots, computer agents and virtual assistants.

Deanna D. Sellnow is a Professor of strategic communication at the University of Central Florida. Her research focuses on strategic instructional communication in a variety of contexts including risk, crisis, and health. She has conducted numerous funded research projects and has published in national and international journals.