International Journal of Human–Computer Interaction

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/hihc20

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INTERNATIONAL JOURNAL OF HUMAN–COMPUTER INTERACTION
https://doi.org/10.1080/10447318.2020.1801227

My Teacher Is a Machine: Understanding Students' Perceptions of AI Teaching Assistants in Online Education

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ABSTRACT

An increase in demand for online education has led to the creation of a new technology, machine teachers, or artificial intelligence (AI) teaching assistants. In fact, AI teaching assistants have already been implemented in a small number of courses in the United States. However, little is known about how students will perceive AI teaching assistants. Thus, the present study investigated students' perceptions about AI teaching assistants in higher education by use of an online survey. Primary findings indicate that perceived usefulness of an AI teaching assistant and perceived ease of communication with an AI teaching assistant are key to understanding an eventual adoption of AI teaching assistant-based education. These findings provide support for AI teaching assistant adoption. Based on the present study's findings, more research is needed to better understand the nuances associated with the learning experience one may have from an AI teaching assistant.

In 2016, one professor at the Georgia Institute of Technology in the United States introduced Jill Watson, the first AI (artificial intelligence) teaching assistant, to his class. This AI teaching assistant was first developed for the professor's online Knowledge-Based Artificial Intelligence (KBAI) class. The AI teaching assistant was built based on IBM's Watson platform, and it was primarily designed to answer students' questions from the online forums in the KBAI course. While some students questioned the teaching assistant because of her fast responses, the identity of the teaching assistant was not known until the professor revealed it at the end of the semester.

While the past decade witnessed the fast development of online education from a traditional face-to-face education, the current technological era takes one step further. The introduction of AI teaching assistants signal that the realm of education has begun its new era by incorporating nonhuman agents as tutors, assistants, advisors, and/or teachers, so-called "machine teachers." Although human teachers may not be completely replaced by machines, machines have a great potential to serve diverse roles in education. As Edwards and Edwards (2017) note, "machines increasingly are being designed to teach and to learn through interaction and to be responsive to natural teaching and learning methods employed by their human partners" (p. 487). Thus, the new era of education where machines become part of the educator pool is fast approaching.

This reality gives rise to several important questions. For instance, what relationships exist between machine teachers and student learning outcomes, and how do these relationships compare to human teachers? What is a machine teacher's role in classroom management? Before addressing these questions and many others, it seems prudent to understand the degree to which people are prepared to accept the notion of machine teachers. While technology is well advanced to create an AI teaching assistant, little is known about how students would perceive the AI teaching assistant.

Considering that the notion of AI in education is fairly new, it is important to understand this phenomenon from the perspective of technology users, particularly students. To build this area of research, the present study examines how perceptions about AI teaching assistants are related to students' attitudes toward AI-based education. Specifically, the study focuses on the perceived usefulness and ease of communication with AI teaching assistants through the theoretical framework of the Technology Acceptance Model (TAM).

The following paper features a review of literature relevant to the uses of technology in educational settings, the theoretical framework of the TAM, and the TAM's relevance to machine teachers. Then, a description of the current study's method and results that are derived from the study's design is provided. A discussion of the findings is then presented, with implications for research and practice, along with directions for future research.

1. Use of technology in education

1.1. Background: Technology in education

The use of technology in the classroom is not a novel idea. However, the particular technologies used continue to evolve as new affordances become available (Sellnow & Kaufmann, 2018). For example, the practice has moved from teaching math computations using an abacus, to a calculator, and now to the computer. Lectures were reinforced with notes on

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chalkboards, then whiteboards, and now computers and smartboards. Whereas formal presentations were once accompanied by graphics displayed on poster boards, they are now enhanced with computerized slideshows and delivered in face-to-face and online environments.

A major trend toward delivering entire courses online emerged with the introduction of the World Wide Web in 1989 (McPherson, 2009). Since then, much debate has ensued about the value of online education. This debate continues today with reports that only 29% of faculty accept online learning as a valid delivery method (Online Learning Consortium, 2015). Nevertheless, the trend toward online learning has grown to include entire programs and even entire universities (Kelly & Westerman, 2016). In fact, a 2017 survey conducted by the U.S. Department of Education reports that 33.7 percent of college students took at least one distance education course (Department of Education, 2018). These percentages will no doubt rise as a result of delivering instruction remotely during the COVID-19 global pandemic.

A good deal of research has examined whether and how to teach most effectively online. These studies focus on pedagogies such as immediacy (Al Ghamdi et al., 2016), classroom climate (Kaufmann et al., 2016), student engagement (Walther, 2011), and learning outcome comparisons to other delivery modes (Sellnow-Richmond et al., 2019).

In facilitating effective online learning, one particularly fruitful area of research focuses on the importance of social presence and self-disclosure as they are found to maintain positive teacher-student relationships, improve student learning performance, and build a sense of community among students (e.g., Shea et al., 2006; Song et al., 2019; Sung & Mayer, 2012). In particular, strong social presence of their teacher is found to facilitate more positive learning experiences in online classes (Kim et al., 2016). Further, Song et al. (2016) found that the effect of self-disclosure about teachers' basic information in the context of online education had more weight than that in a traditional face-to-face educational context. Focusing on the importance of teacher self-disclosure and social presence, Song et al. (2019) found that teacher self-disclosure fosters social presence of teachers, which eventually facilitates positive learning experiences in online education. In essence, fostering positive social presence is critical to student satisfaction in online courses.

To further enhance meaningful experiences in student learning, more advanced technologies, such as virtual reality (VR) and augmented reality (AR) technologies, have been employed in educational contexts. For instance, researchers have incorporated game-based learning, location-based learning, and role playing in AR platforms to facilitate more vivid learning experiences (Wu et al., 2012).

1.2. Social robots in education

Moreover, there has been an increased use of social robots in education. Social robots are autonomous machines that generally follow social behavior norms and interact with humans in various settings (Gockley et al., 2007). Although robots were first introduced in classrooms in the 1980s, they are becoming increasingly popular today (Johal et al., 2018). In educational settings, social robots may take on the role of a teacher, tutor, peer, or even a care-seeking companion (Belpaeme et al., 2018; Mubin et al., 2013; Sharkey, 2016). As has been the case with debates surrounding the value of delivering courses fully online so, too, has the idea of using robots in instruction produced divergent opinions among educational researchers (Javaheri et al., 2019). Some argue, for example, that students prefer a human instructor even though knowledge recall is significantly better when delivered by a robot (Li et al., 2015). Other arguments range from issues of cost, teacher training, and applicability (Johal et al., 2018).

In response to such concerns, a good deal of the literature documents positive effects of social robots in educational settings. A group of researchers (A. Edwards et al., 2016) found social robots to be credible sources of information related to student learning. In particular, students perceived social robots to be capable of appropriately relaying information in educational settings. In another study (E. Park et al., 2011), when educating participants on a certain topic, a robot tutor that provided positive feedback was perceived as attractive and acceptable. In a similar vein, social robots have been used to help homebound students engage in a real classroom environment and interact with classmates and professors synchronously (Double Robotics, 2017). In all, these studies support the review of research showing that social robots in educational settings have positive effects on student learning (Belpaeme et al., 2018).

While social robots have the potential to facilitate student learning outcomes, there are a few aspects that may require particular attention in order to utilize robots in education more effectively. Castellano et al. (2013) identified two factors in human-robot interaction that are crucial to student learning: empathy and engagement. Castellano et al. argue that robotic tutors need to develop the ability to use empathic messages as well as other social cues to create social bonding between humans and machines. Li (2015) found that among different forms of robotic technologies, a robot that is physically present can deliver more persuasive messages and receive more attention than a virtual agent (e.g., virtually present robot on a screen). Further, Li et al. (2015) found interesting patterns regarding robot use in online education contexts. They found that a video of a human instructor and that of an animated robot have similar effects on students' knowledge recall, but a video of a real robot has weaker effects on participants' recall performances.

In sum, although not always the case, most research on robots in education has shown promising ways that can facilitate effective learning experiences. It is, of course, noted that the positive effects of utilizing robots, or machines in a border term, may vary depending on a few factors such as types/forms of machines and content. However, considering that machines could be helpful in facilitating effective teaching, such as standardized teaching format and consistent content delivery, particularly in times when health and safety may put teachers and students at risk in face-to-face settings, there seems to be reason why the notion of machine teachers needs to be considered in education.

2. Machine teachers and the technology acceptance model

2.1. Machine teachers

As technology continues to develop, it is likely that the future of education would eventually adopt machine teachers in diverse roles (e.g., teaching assistant, instructor, academic advisor). Although the present study does not intend to firmly define the notion of machine teachers yet, it appears to be important to initiate conceptualizing it as the new era of education unfolds. Machines are referred to as technologies that feature a certain level of agency in that they can play a distinct role during an interaction (Fischer, 1990; Guzman, 2018). Teachers can be understood as someone that encourages and empowers others to improve affective, cognitive, and behavioral learning through acquisition of knowledge, development, and molding of virtues (Bloom, 1956). Based on these two concepts, a *machine teacher* can be broadly 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.

Machine teacher is an umbrella term that can appear in a variety of forms. In particular, they can appear either as embodied or disembodied agents. Embodiment refers to the idea that the system requires a physical instantiation or a physical body (Pfeifer & Scheier, 1999). An embodied machine teacher can be physical, virtual, or even mixed. Physically embodied machines can be constructed from metal, plastic, or other materials (Li et al., 2015). Robots like NAO or Sony AIBO are examples of physically embodied machines that have been applied in the face-to-face pedagogical context. Virtually embodied machine teachers refer to those computer-generated agents that have a visually identifiable body, which appears on a screen only (Li, 2015). For instance, many online agents are rendered in the form of animated characters, such as the early Microsoft's Clippy, an intelligent user interface for Microsoft office that assisted users by way of an interactive animated character. Machine teachers can also appear in a mixed form that incorporates both physical and virtual agents. That is, some physically embodied robots are equipped with an electronic tablet that presents embodied virtual agents on a screen (e.g., telepresent robots). Unlike embodied machines, disembodied machine teachers do not have any visible or physical instantiation but interact with others in unique ways. Specifically, chatbots, software agents, or interface agents can afford to interact with humans through text-based or voice-based messages without requiring a visible or physical form. For instance, in the current market, Microsoft's Little Ice (conversational agent; chatbot) and Google Duplex can all be considered as disembodied agents.

Considering the increased demand and popularity of online classes in higher education (Allen & Seaman, 2017), it is expected that there will be a great need for machine teachers in the near future. In particular, given the nature of an online environment, either disembodied or virtually embodied machine teachers would most likely be needed. However, little is known about how students might respond to the idea of machine teachers. In this regard, the present study examines students' perceptions about machine teachers through the theoretical framework of the Technology Acceptance Model (TAM).

2.2. Technology Acceptance Model

The Technology Acceptance Model (TAM) is generally used to explain how individuals accept and use various technologies (Davis, 1989; Davis et al., 1989). Specifically, the TAM posits that adoption of technologies is influenced by an individual's behavioral intentions to use a particular technology.

Key to the TAM are both an individual's perceived usefulness and perceived ease of use of the technology. Perceived usefulness refers to the degree to which an individual views a technology as having particularly enhancing capabilities, whereas perceived ease of use refers to how simple and carefree it would be for an individual to interact/engage with a specific technology (Davis, 1989). The extant body of research has found perceived usefulness to have a stronger link to intention to adopt a new technology as compared to perceived ease of use (Abdullah & Ward, 2016; Davis, 1989), but both play a vital role in an individual's intention to adopt a new technology. Additionally, researchers have continuously found perceived ease of use as a direct factor influencing perceived usefulness (Abdullah & Ward, 2016; Park & Chen, 2007), which is aligned with the model presented by Davis et al. (1989). These two concepts have been shown to be directly related to attitudes toward a particular technology. That is, the more useful the technology is perceived to be as well as the easier it is to use the technology, the more likely that individuals would develop positive attitudes toward the particular technology (Davis et al., 1989). Then, positive attitudes toward using a particular technology and perceived usefulness are directly related to an individual's behavioral intention to use the technology, which would affect an individual's actual behavior of adopting the new technology.

The TAM has been applied to a variety of different technologies, including popular social technologies such as wireless Internet (Lu et al., 2003), smartphones (Park & Chen, 2007), social networking sites (Choi & Chung, 2013), and virtual reality (Lin & Yeh, 2019; Sagnier et al., 2020). These previous applications of the TAM illustrate the role that perceived usefulness and perceived ease of use play in adopting particular technologies in different contexts.

In educational contexts, the TAM has been utilized to understand educational technologies such as e-Portfolios for learning (Abdullah et al., 2016), educational wikis (Liu, 2010), electronic courseware (N. Park et al., 2007), and social media for educational purposes (Mazman & Usluel, 2010). Much like previous research that has applied the TAM, all of these studies highlight the role that perceived usefulness and perceived ease of use play in adopting educational technologies in a variety of ways. For example, a study (Abdullah et al., 2016) found the effects of both students' perceived usefulness and perceived ease of use of e-portfolios on an individual's behavioral intention. Additionally, Abdullah and Ward (2016) completed a meta-analysis using the TAM to better understand the adoption of e-learning, or tools that utilize online technologies for instructional purposes.

More germane to the particular context of the present investigation, although very limited, are a couple of studies that have adopted the TAM to understand AI-driven assessment tools in eLearning settings (e.g., Cruz-Benito et al., 2019; Sánchez-Prieto et al., 2019). In particular, Sánchez-Prieto et al. (2019) proposed several arguments that highlight key factors of the TAM in the understanding of AI-driven assessment among teachers. Based on the core of the TAM, Sánchez-Prieto et al. argues that perceived usefulness and perceived ease of use are positively related to the teachers' intention to use AI-driven assessment in eLearning, which will eventually lead to the actual adoption. Although these studies are limited to the conceptual propositions without empirical evidence, they highlight the theoretical underpinning of the TAM in the understanding of AI-related educational experiences.

Taken together, the present study takes an initial approach to understand how college students would perceive the idea of machine teachers. Considering that it might be too unrealistic for some students to imagine having a machine as the primary instructor of their own class, the current study focuses on a machine teacher functioning as a teaching assistant. For the same reason, the study focuses on a machine teacher as a disembodied AI agent because students may have some familiarity with disembodied AI, considering the popularity of voice-based AI (Statista, 2019), such as Apple's Siri. In this regard, the study examines students' perceptions of an AI teaching assistant. Taken together, the study proposes the following hypotheses based on the original theoretical framework of the TAM. See Figure 1.

H1: Perceived ease of communication with an AI teaching assistant will positively lead to perceived usefulness of an AI teaching assistant.

H2a-b: (a) Perceived usefulness of an AI teaching assistant and (b) perceived ease of communication with an AI teaching assistant will lead to positive attitudes toward using an AI teaching assistant.

H3: Positive attitudes toward using an AI teaching assistant will lead to intention to adopt AI teaching assistant-based education.

H4: Perceived usefulness of an AI teaching assistant will lead to intention to adopt AI teaching assistant-based education.

3. Methods

3.1. Participants

Initially, a total of 349 undergraduate students from communication courses at a large public university in the U.S. responded to this study. To ensure the study received data of good quality, a few steps were taken to filter out unusable data. First, given that the survey was distributed to multiple classes (see the procedure section), a question was asked to indicate whether the participants have taken this survey before. Twenty-three individuals were identified to have taken it before; thus, these second-time responses were eliminated. Second, an attention check was performed in the middle of the survey to ensure that participants read the survey questions accurately. Five individuals failed; therefore, they were eliminated from the sample.

After the screening process, the final sample consisted of 321 eligible participants. The average age was 21.52 years (SD = 4.16). There were more females (n = 209: 65.1%) than males (n = 112: 34.9%) in the sample. Majority of the participants identified themselves as Caucasian (n = 167: 52%), followed by Hispanic or Latino (n = 71: 22.1%), African American (n = 54: 16.8%), and other racial/ethnic identities (n = 29: 9%). Regarding class standing, the sample included 17 freshmen (5.3%), 80 sophomores (24.9%), 152 juniors (47.4%), and 72 seniors (22.4%).

3.2. Procedure

A questionnaire was distributed with a university-licensed online survey tool (www.qualtrics.com). The primary researcher contacted instructors of undergraduate courses and asked whether they would be willing to share the research participation opportunity with students. Upon approval, a link was sent to potential participants, and they were asked to complete the survey online.

Once participants accessed the survey, they were asked to read and acknowledge the informed consent prior to proceeding to complete the survey. At the beginning of the survey, participants' attitudes toward new technologies (e.g., Apple's Siri, Amazon's Alexa) were assessed. Then,

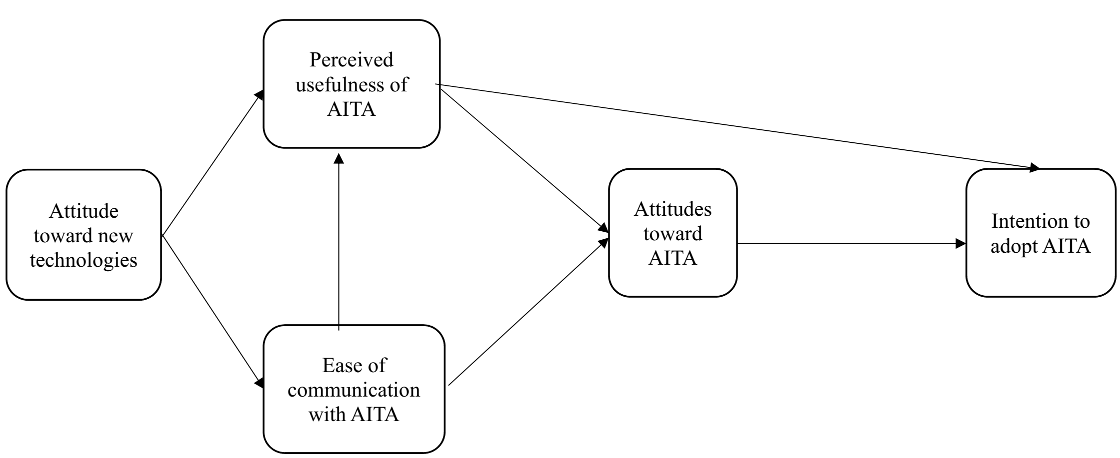

Figure 1. Proposed research model.
Note: AITA refers to Artificial Intelligence Teaching Assistant.

they were led to read an article about an AI teaching assistant in higher education. This article was the actual article that was previously published in *The Washington Post*. The article was about an AI teaching assistant, which was built by a professor at a university in the U.S. Mostly, the article described the AI teaching assistant that was used for the class and its role for the class. In order to avoid a situation where participants may skip the page without reading the article, a timer was set on that article page. This function did not allow participants to go to the next page for a certain duration of time, which ensured that participants read the article as part of this research participation.

After reading the article, participants were asked to complete a set of questions, which asked about their perceptions about the AI teaching assistant they learned about from the article. At the end of the survey, participants were redirected to a separate website, independent from the original survey, where they could provide their name and course information for extra credit purposes. Confidentiality was guaranteed.

3.3. Measures

Before the stimulus, *attitudes toward new technologies* (α =.89) were measured with three items (adopted from Nass et al., 1994). 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 interpretive roles (e.g., editorial writers, newspaper reporters, novelists)." Responses were obtained on a 6-point scale (1 = *Very Uncomfortable*, 6 = *Very Comfortable*).

After the stimulus, a set of questions were asked to assess participants' perceptions about the AI teaching assistant. *Perceived usefulness of an AI teaching assistant* (α = .94) was measured with four items (e.g., "Using an AI teaching assistant would increase my learning productivity," and "… would enhance my learning effectiveness"). *Perceived ease of communication with an AI teaching assistant* (α = .89) was measured with four items (e.g., "It would be easy to learn how to communicate with an AI teaching assistant," and "Interacting with an AI teaching assistant would not require a lot of my mental effort"). Items for both perceived usefulness and ease of communication were modified from Davis (1989). Responses were obtained on a 7-point Likert-type scale (e.g., 1 = *Strongly Disagree*, 7 = *Strongly Agree*).

Attitudes toward using an AI teaching assistant (α = .95) were measured with five items (e.g., "bad – good," and "unfavorable – favorable") on a 7-point semantic differential scale. Items were adopted from Davis (1993). *Intention to adopt AI teaching assistant-based education* (α = .95) was measured with three items (e.g., "If an AI teaching assistant-based online class is available, I would consider taking the class," and "… I would be interested in taking the class."). Items were adopted from (Choi & Ji, 2015), and responses were obtained on a 7-point Likert-type scale (e.g., 1 = *Strongly Disagree*, 7 = *Strongly Agree*).

4. Results

Before conducting the hypothesis testing, a control variable was considered. Given that the notion of an AI teaching assistant is an advanced concept of technology, individuals who are generally open to new technology might be in favor of an AI teaching assistant than others who are somewhat resistant to adopting new technology in general. In this regard, overall attitudes toward new technologies were entered as a controlling variable in the data analyses.

In order to test the proposed hypotheses, including an overall model fit for the theoretical framework of the TAM, structural equation modeling was employed using Mplus 7 (Muthén & Muthén, 2015). Maximum likelihood estimation was used to estimate the proposed research model. Results suggest that the hypothesized model did not show a goodness of fit for the data, X^2 (3, N = 321) = 29.02, p < .001, CFI = .97, TLI = .89, $RMSEA$ = .16, $SRMR$ = .03. The process of indices modification was used to improve the model. In Mplus, standardized residuals for correlations were reviewed to see whether the model under-predicted any relationships. After iterative modification, perceived ease of communication with an AI teaching assistant was correlated with users' intention to adopt AI teaching assistant-based education. Although this link was not originally identified in the TAM, which is why the present research did not include it in the original testing model, this link was noted in previous research (Abdullah et al., 2016). The modified model showed that it had a goodness of fit for the data, X^2 (2, N = 321) = 29.02, p > .05, CFI = .996, TLI = .98 $RMSEA$ = .07, $SRMR$ = .03.

Specifically, controlling for attitudes toward new technologies, perceived ease of communication with an AI teaching assistant positively predicted perceived usefulness of an AI teaching assistant (B = .63, p < .001), supporting H1. Regarding H2a-b, both perceived usefulness of an AI teaching assistant (B = .55, p < .001) and perceived ease of communication with an AI teaching assistant (B = .35, p < .001) showed positive relationships with users' attitudes toward using an AI teaching assistant. With regard to H3, attitudes toward using an AI teaching assistant (B = .50, p < .001) positively led to intention to adopt AI teaching assistant-based education. For H4, perceived usefulness (B = .25, p < .001) positively and directly predicted intention to adopt AI teaching assistant-based education. Thus, all hypotheses were supported. See Figure 2.

5. Discussion

The present study examined students' perceptions about an AI teaching assistant in higher education. Primary findings indicate that perceived usefulness of an AI teaching assistant and perceived ease of communication with an AI teaching assistant positively predict favorable attitudes toward using an AI teaching assistant, which consequently leads to stronger intention to adopt AI teaching assistant-based education. Moreover, the study reveals that perceived usefulness and ease of communication directly predict intention to adopt AI teaching assistant-based education.

5.1. Contributions and implications

The current study provides important contributions to and implications for research and practice. First, the study makes theoretical contributions to research on the TAM.

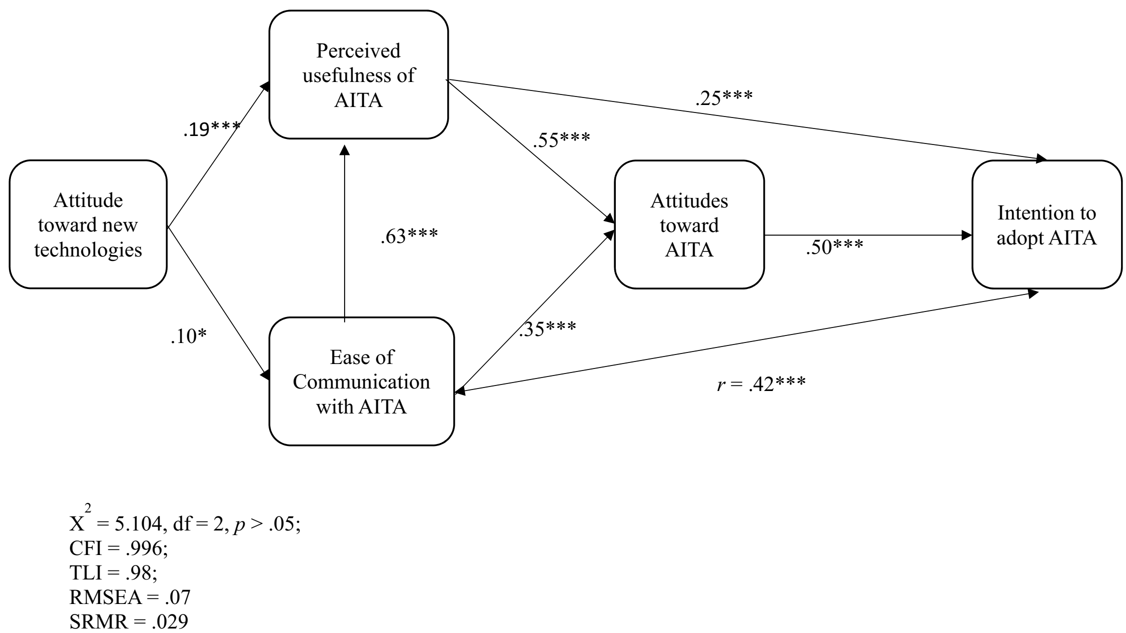

Figure 2. Final model.
Note 1: AITA refers to Artificial Intelligence Teaching Assistant. Note 2: * p <.05; ** p <.01; *** p <.001.

The TAM is a useful framework that is used to understand adoption of new technologies in diverse contexts, such as the smartphones (Park & Chen, 2007), social media (Choi & Chung, 2013), and virtual reality (Lin & Yeh, 2019; Sagnier et al., 2020). Although very limited, the TAM has been also employed to understand the adoption of AI-based assessment in education (Cruz-Benito et al., 2019; Sánchez-Prieto et al., 2019). However, the use of TAM in these studies was limited to proposing theoretical arguments without empirical support. To our knowledge, the present study is one of the first instances that empirically tested the TAM being utilized to understand the adoption of machine teachers. As reported in the result section, the findings fully support the underpinning of the TAM regarding the machine teacher, more specifically in the AI-based education context. Overall, the study's findings provide more supporting evidence for the TAM's explanatory power. That is, the TAM can be, and has been, applied to better understand how individuals adopt new technologies in diverse contexts, and it ultimately expands the scope of the TAM.

Second, the results of this study point to significant implications for instructional communication. As mentioned earlier, while technological skills are well advanced to create machine teachers, there is little understanding about how students would perceive the idea of machine teachers. Acknowledging that many educators remain skeptical about the value of AI in the classroom (Johal et al., 2018), as well as the trend that robots are here to stay (Edwards & Edwards, 2017; McDowell & Gunkel, 2016), the present study provides baseline information that helps educators better understand how students may perceive and react to them. Given that much research exists pointing to the value of AI in educational contexts as it addresses cognitive and behavioral learning outcomes (e.g., Brown et al., 2013; Chollet et al., 2015; A. Edwards et al., 2016; Edwards et al., 2019; Li et al., 2015; Wu et al., 2012), perhaps addressing student affect toward the use of AI in education is the missing link to convince skeptics and those that may currently feel apprehensive.

Next, in an era of declining financial resources for higher education in the United States, machine teachers may afford an opportunity to address instructional needs in cost effective ways in the long run. To clarify, higher education administrators attempt to address student demand for courses by increasing enrollment caps, as well as by employing adjunct instructors and graduate teaching assistants (GTA). In fact, "between 2000 and 2017, total undergraduate enrollment in degree-granting postsecondary institutions increased by 27%" and is projected to increase another 3% by 2028 (Department of Education, 2019). Typical class sizes for introductory level courses at universities may range from 150 to 300 students (Willingham, 2019). For many departments, financial and human resources are stretched to a breaking point. There are limits to how many adjuncts and GTAs can be staffed as instructors without jeopardizing accreditation (Stenerson et al., 2010). Some programs have attempted to address the problems by employing undergraduate teaching assistants (UTAs) (Reynolds et al., 2014); however, based on the results of this study, it seems reasonable to consider ways in which AI teaching assistants could play an important role in addressing these needs as well.

The present research findings also point to the importance of training for effective use of machine teachers, particularly AI teaching assistants. Although students' attitudes toward using AI teaching assistants might be generally positive, this might only be true if students and teachers feel at ease with communicating with AI teaching assistants. To be successful, then, teachers must be trained in how to use an AI teaching assistant in ways that foster immediacy and social presence (Kaufmann et al., 2016; Kim et al., 2016; Song et al., 2019). Research confirms that when instructors appear uncomfortable employing a particular pedagogical strategy, student attitudes are also negative (e.g., Liu et al., 2016; Tichavsky et al., 2015). Thus, teacher certification programs ought to add curriculum not only to teach preservice instructors how to use AI effectively, but also to realize the value that AI teaching assistants can bring to the teaching and learning experience (Edwards & Edwards, 2017; Edwards et al., 2018, 2019). Moreover, practicing teachers must be offered ongoing training in the form of workshops, webinars, and online modules (Al-Balushi & Al-Abdali, 2015; Ramírez-Montoya et al., 2017; Tarhan, 2015). Failing to do so is essentially setting teachers up for failure, not because AI teaching assistants are ineffective, but because teachers are uninformed about pedagogical best practices in employing them as such.

Finally, the study suggests practical implications for developing machine teachers. The study acknowledges that developing a program that utilizes machine teachers can be costly at first. In order to effectively maximize their use, it is important to create machine teachers that are favorably accepted by both students and teachers. So, universities can adopt the program repeatedly as long as the course exists in their schedule. In this regard, the study's finding highlights that machine teachers should be perceived to be useful and easy to communicate with, as these aspects would eventually lead to the actual adoption. It is important to note that the present study does not argue that machine teachers will replace the entire role of human teachers. However, it might be true that human teachers can receive some help from these machine teachers in certain areas (e.g., repeated tasks on course management website), as they can appear in a variety of forms with diverse functionalities.

5.2. Limitations and future research directions

While this study revealed important findings and implications for using AI in education, the study recognizes some limitations that should be considered when interpreting the patterns of the results. First, because the study used a short article to inform participants of an AI teaching assistant, participants had a one-time, limited exposure to the idea of an AI teaching assistant based on the way the article was written. Although the selected article was written in an objective manner, which simply describes the AI teaching assistant without biased perspectives, it might be possible that some students may have perceived the framing of the story as being positive or negative. Also, learning about the AI teaching assistant by reading the story, rather than directly interacting with it, might have limited participants' perceptions about the AI teaching assistant. If participants have continued and direct interactions with the AI teaching assistant in the real world, their perceptions may change.

As such, future researchers should examine students' responses to direct exposures of an AI teaching assistant. This can be accomplished in a variety of ways. For example, one could conduct a lab experiment to see how students respond to AI teaching assistants. This method allows the researchers to manipulate key variables (e.g., AI teaching assistant's communication styles) to better understand which aspects of an AI teaching assistant would facilitate more effective learning experiences. It would also be meaningful to conduct a longitudinal study to understand whether and/or how student perceptions would change over time. Qualitative methods such as interviews, focus groups, and ethnographies can also prove to be beneficial. Interviews and focus groups can prove direct verbal or written responses from students about their experiences with AI teaching assistants. Themes that emerge from these methods may help researchers better understand underlying mechanisms that may play a role in understanding how individuals respond to AI teaching assistants. Moreover, ethnographies may be of interest, as researchers could examine how students respond to AI teaching assistants in the classroom. By immersing oneself in a classroom that utilizes AI teaching assistants, the research can record first-hand experiences of this phenomenon. Thus, there is a strong call for more research in order to fully capture the idea of how students may respond to this technology over time.

Next, students recruited for this study were from a large pubic university that offers both online and offline courses. Thus, it is unclear whether their responses and perceptions about AI teaching assistants would be the same as those who only have online education experiences. It might be possible that students enrolled at a fully online university are comfortable enough with the use of technology in their education; thus, they might be more accepting of the idea of AI teaching assistants. In order to fully investigate this, future research should consider collecting data from both a fully online university as well as a traditional university to examine the potential differences.

Another limitation is that the study only focused on one particular type of machine teachers, an AI teaching assistant that appeared as a disembodied agent. As mentioned earlier, machine teachers can exist in a variety of forms including disembodied and embodied, and they can vary in degrees of anthropomorphism, which is the attribution of humanlike behaviors and characteristics to nonhuman agents (Guthrie, 1993). In order to fully understand the best and optimal adoption of machine teachers in education, more research is needed. For example, it would be interesting to see if there is a specific type of machine teacher that is preferred among students. Future researchers should also observe whether differences exist in the learning experiences based on these different types of machine teachers. It may be possible that students learn more with a specific type, and this would be important information to know for future implementations of machine teachers in classrooms.

Lastly, future research should consider potential individual differences such as perceptions about AI, learning styles, personality, sex, etc. Although the idea of AI teaching assistants brings about much efficiency in education, it does not guarantee that everyone will enjoy this. For example, understanding how students view AI could be worth investigating as the perceptions of AI in general might affect how they would view AI in educational settings. Additionally, prior experiences with AI may also influence students to be either apprehensive or welcoming of AI teaching assistants. In this regard, future research should further investigate potential individual differences in adopting this new technology in education.

6. Conclusion

The present study investigated students' perceptions about AI teaching assistants in higher education. Primary findings indicate that perceived usefulness of an AI teaching assistant and perceived ease of communication with an AI teaching assistant play an important role in the understanding of AI teaching assistant-based education. Based on the current study's initial findings, future researchers are encouraged to expand this area of research by replicating it with different student populations and teachers. Depending on the level of education (e.g., college vs. high school), students' perceptions about an AI teaching assistant might differ. Additionally, it is equally important to understand how teachers would perceive the idea of AI teaching assistants, or more broadly machine teachers, in order to implement this new technology in education. Moreover, AI instruction may provide an effective means for delivering instruction when current events prohibit face-to-face human interaction. Therefore, the present study calls for a strong need to further advance this area of research.

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