



New Review of Hypermedia and Multimedia

ISSN: 1361-4568 (Print) 1740-7842 (Online) Journal homepage: http://www.tandfonline.com/loi/tham20

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To cite this article: Hosun Yoo, Ohbyung Kwon & Namyeon Lee (2016) Human likeness: cognitive and affective factors affecting adoption of robot-assisted learning systems, New Review of Hypermedia and Multimedia, 22:3, 169-188, DOI: 10.1080/13614568.2016.1152312

To link to this article: https://doi.org/10.1080/13614568.2016.1152312



Published online: 16 Mar 2016.



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Human likeness: cognitive and affective factors affecting adoption of robot-assisted learning systems

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ABSTRACT

With advances in robot technology, interest in robotic e-learning systems has increased. In some laboratories, experiments are being conducted with humanoid robots as artificial tutors because of their likeness to humans, the rich possibilities of using this type of media, and the multimodal interaction capabilities of these robots. The robot-assisted learning system, a special type of elearning system, aims to increase the learner's concentration, pleasure, and learning performance dramatically. However, very few empirical studies have examined the effect on learning performance of incorporating humanoid robot technology into elearning systems or people's willingness to accept or adopt robotassisted learning systems. In particular, human likeness, the essential characteristic of humanoid robots as compared with conventional e-learning systems, has not been discussed in a theoretical context. Hence, the purpose of this study is to propose a theoretical model to explain the process of adoption of robotassisted learning systems. In the proposed model, human likeness is conceptualized as a combination of media richness, multimodal interaction capabilities, and para-social relationships; these factors are considered as possible determinants of the degree to which human cognition and affection are related to the adoption of robot-assisted learning systems.

ARTICLE HISTORY

Received 23 March 2015 Revised 15 July 2015 Accepted 14 September 2015

KEYWORDS

Robot-assisted learning; human likeness; humanoid robots; para-social relationships; multimodal capability; media richness; technology adoption

1. Introduction

Advances in robotic technologies, especially developments that give robots humanoid characteristics, have made use of robots more popular for many purposes, including support of learning (Kanda, Hirano, Eaton, & Ishiguro, 2004). Over the past decade, robots have been utilized as learning assistants in many educational settings, and their pedagogical effects on learning have been investigated (Han & Kim, 2009; Kanda, Sato, Saiwaki, & Ishiguro, 2007). Research has shown that humanoid robots provide learners with a more natural interface in terms of human likeness, along with richer representation and better understanding, than non-humanoid robots (Reeves et al., 2004, Tinwell et al. 2011). Developers of robot-based learning systems that incorporate use of humanoid

robots expect that these characteristics may encourage learners and their parents to adopt robot-based learning systems more readily.

However, the link between robot-assisted learning systems and their acceptance requires investigation. In particular, no empirical studies have been conducted that fully explain the effects of human likeness of robots on users' propensity to adopt robot-assisted learning systems. Although some researchers have examined users' perceptions of robots (Lee, Shin, & Sundar, 2011; Shibata, Wada, & Tanie, 2004), these studies focused on individual impressions of specific robots. Moreover, the results of these studies do not reflect the psychological influence on learners of the unique characteristics of robot service via ubiquitous sensor networks in educational settings. Since use of humanoid robot technology in learning settings is still in the initial stages of development, empirical evidence about the effectiveness of humanoid robots will be very useful for researchers and practitioners who want to develop more easily adoptable robot-assisted learning systems.

In this study, an integrated theoretical model is proposed in which factors related to human likeness that affect learners' performance expectations and adoption of robotassisted learning systems are identified. Human likeness is examined in the context of learning systems with reference to media richness (MR) theory (Daft & Lengel, 1986; Liu, Liao, & Pratt, 2009) and para-social relationship (PSR) theory (Levy, 1979; Rubin, Perse, & Powell, 1985) in order to elucidate users' perceptions of humanoid robots. To bridge the gap between perceptions of human likeness and adoption of robot-assisted learning systems, flow theory (Csikszentmihalyi & Csikszentmihalyi, 1992; Koufaris, 2002) and the technology acceptance model (TAM) (Davis, 1989, Koufaris, 2002; ŠUmak, HeričKo, & PušNik, 2011; Venkatesh, Morris, Davis, & Davis, 2003) are utilized in the development of the proposed model. From these three theoretical perspectives, empirical testing is conducted and theoretical and practical implications are drawn from the results.

This paper is organized as follows. Section 2 provides the theoretical background relevant to robot-assisted learning acceptance, outlines the proposed research model, and states the hypotheses. Section 3 describes the procedures and methodology used in this study. Finally, Sections 4 and 5 present the results of the analysis of survey data and discuss these results.

2. Theoretical background and hypotheses

2.1. Robot-assisted learning

Alongside various advances in information technology, innovative e-learning systems have been developed. For example, mobile learning systems (m-learning) enable learners to be educated anywhere and anytime through their portable electronic devices. Ubiquitous (u)-learning systems, including embedded tutoring and context awareness functionality, are provided within many mobile devices along with various features to make learning systems more intelligent and personal (Hwang, Tsai, & Yang, 2008). To make interfaces more natural, advanced user interface technologies such as augmented reality, wearable computing technology, and multimodal interfaces are being considered in the development of u-learning systems.

Robot-assisted learning systems can be seen as a subset of u-learning systems. In robotassisted learning, a humanoid robot acts as an intelligent computer. Sensors built into the robot acquire contextual information in real time, which is then used to provide individualized learning. Various multimodal features, including voice, sound, color, light, screen displays, and even gestures, are used to facilitate learning. Although these features are also available with conventional u-learning systems, humanoid robots may be perceived as more natural than PCs, smart phones, dedicated kiosks, or any other popular devices commonly used in u-learning systems. Humanoid robots are also more attractive; they have the advantage of greater conversational flow and familiarity to learners due to their likeness to humans (Tinwell et al. 2011). Thus, robot-assisted learning systems may be considered an advanced form of u-learning systems.

In most cases, the role of the robot in robot-assisted learning systems is a teaching assistant rather than a tutor. Han (2010) suggested that teaching assistant robots may be useful in innovative educational settings for learners to obtain knowledge and skills under the supervision and support of a teacher both inside and outside the classroom. Also, in robot-assisted learning systems, robots can be used as educational tools and act as a sort of classmate of the children.

The effects of the features of robot-assisted learning systems on learners' adoption behavior have not been empirically determined. Some studies have been conducted on adoption of robots in other fields. However, these studies did not examine the features of robot-assisted learning systems. Fridin and Belokopytov (2014) examined acceptance of socially assistive humanoid robots by preschool and primary school teachers. They found that some cognitive and affective factors affect teachers' intentions to use the robot. Alaiad and Zhou (2014) investigated the factors affecting adoption of healthcare robots. They developed a research model based on the unified theory of acceptance and use of technology (UTAUT). In addition, Stafford, MacDonald, Jayawardena, Wegner, and Broadbent (2014) focused on psychological factors that affect users' intention to use a robot. They suggested that a positive attitude toward the robot increased adoption intention (AI). However, they did not consider the functional features of robots.

Studies on adoption of e-learning systems have proposed several cognitive behavioral models, such as the theory of planned behavior (Ajzen, 1991), TAM (Davis, 1989), and expectation confirmation theory (Bhattacherjee, 2001). These models have been widely used to explain adoption and continuance behavior of users of e-learning technologies (ŠUmak et al., 2011). The TAM has been utilized in information technology acceptance and usage research for nearly two decades. In this model, two independent factors, perceived performance (or usefulness) and perceived ease of use, are the main determinants of technology adoption.

In the context of a new e-learning technology, various factors may influence users' decision-making as to how and when they will use a particular technology. According to the meta-analysis of ŠUmak et al. (2011), the quality of information (Alkhattabi, Neagu, & Cullen, 2011) and e-learning technology systems influences acceptance via perceived usefulness and perceived ease of use. In this study, perceived usefulness is equated with the construct known as performance expectancy (PE), and perceived ease of use is equated with effort expectancy (EE).

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Figure 1. Conceptual framework.Note: MC: multimodal capability; MR: media richness; PSR: para-social relationship; PE: performance expectancy; EE: effort expectancy; CON: concentration; AI: adoption intention.

Figure 1 shows the proposed combined model for use in the context of robot-assisted learning. Intention to adopt robot-assisted learning was evaluated using revised versions of the constructs of the UTAUT2 modified from that originally proposed by Venkatesh et al. (2003), flow theory (Daft & Lengel, 1986; Koufaris, 2002), MR theory (Daft & Lengel, 1986; Liu et al., 2009) and the theory of PSRs (Levy, 1979; Rubin et al., 1985). As the figure shows, seven constructs derived from studies using these theories were utilized in the research model put forward in the current study: human likeness factors (multimodal capability (MC), MR, and the PSR), cognitive learning performance factors (PE and EE), one affective learning performance factor (concentration), and AI. We propose that these constructs determine AI. In the context of robot-assisted learning systems, the variables in the combined model were posited as key drivers of intention to adopt robot-assisted learning systems.

2.2. Affective factors: concentration while learning

In flow theory, flow is regarded as one way, along with usefulness and ease of use, to determine the intention of a user to use e-learning technology. Flow is defined as "the state in which people are so involved in an activity that nothing else seems to matter; the experience itself is so enjoyable" (Csikszentmihalyi & Csikszentmihalyi, 1992, p. 4). Flow occurs when an experience is so engrossing and enjoyable that it becomes autotelic, that is, worth doing for its own sake even though it may have no consequence outside itself (Csikszentmihalyi & Csikszentmihalyi, 1992, p. 4).

In flow theory, concentration and other constructs related to hedonic rather than utilitarian values may also explain acceptance of e-learning. Concentration has been found to influence the overall experience of computer users positively (Hoffman & Novak, 1996; Koufaris, 2002; Novak, Hoffman, & Yung, 1998). In the robot-assisted learning context, concentration may also contribute to actual and intended use of robot-assisted learning systems because when users are concentrating hard (i.e. they are in flow), they become absorbed in their activity and better able to focus on e-learning content, which affects individual performance and continuance intention.

A positive association between concentration and adoption of robot-assisted learning systems may be predicted from the results of research on e-learning systems. Research has demonstrated a positive relationship between flow and intention to adopt e-learning systems (Davis, 1989; Van der Heijden, 2004; Koufaris, 2002). Flow is a positive psychological concept related to intrinsic motivational factors (Yang & Lin, 2011) that may be applicable to the context of robot-assisted learning systems. Hence, we hypothesize that:

H1: Concentration while learning is positively associated with intention to adopt robot-assisted learning systems.

2.3. Cognitive factors: PE and EE

When a user is presented with a new learning technology, several factors may influence the decision as to how and when the technology will be used. Cognition-based behavioral models have been widely used to explain users' behavior regarding adoption of e-learning technologies (Ajzen, 1991; Bhattacherjee, 2001; Davis, 1989; ŠUmak et al., 2011). Among these cognition-based behavioral models, the TAM (Davis, 1989) has been frequently used in studies of information technology acceptance and usage for nearly two decades. In this model, perceived usefulness and perceived ease of use are identified as main determinants of technology adoption. In the UTAUT2, which is the model used in this study, PE and EE are representative factors associated with technology adoption or purchase intention; these constructs are equivalent to perceived usefulness and perceived ease of use, respectively. The contribution of these two constructs in explaining adoption behavior has been clearly confirmed by studies based on IT adoption theories.

In previous studies of technology acceptance using the UTAUT2 model, PE and EE are key factors contributing to the success of e-learning (Ong & Lai, 2006, 2007; Ong, Lai, & Wang, 2004). Accordingly, we posit that the positive relationship between these factors and purchase intention will also be applicable in the context of robot-assisted learning. For adoption of e-learning systems, perceived usefulness (or PE) and perceived ease of use (or EE) are determinants of acceptance (ŠUmak et al., 2011). Likewise, we postulate that these factors will be applicable to the context of robot-assisted learning systems. Thus, the following hypotheses are presented:

H2: PE is positively associated with intention to adopt robot-assisted learning systems. H3a: EE is positively associated with intention to adopt robot-assisted learning systems.

The relationship between EE and PE has been examined in many studies using various theories of adoption of information technologies. A positive causal relationship between EE and PE has been identified (Koufaris, 2002; Venkatesh, Thong, & Xu, 2012). This causality is more frequently found in the context of individual information systems than enterprise information systems such as enterprise resource planning and supply chain management, which employees are forced to use. Since use of robot-assisted learning systems is not 174 👄 H. YOO ET AL.

mandatory, they should be classified as individual information systems for the purposes of group communication and problem-solving. Hence, a positive causality between EE and PE is likely to be found in the context of robot-assisted learning systems. Thus, we hypothesize that:

H3b: EE is positively associated with PE while using robot-assisted learning systems.

In addition, past researchers identified a positive relationship between flow and perceived ease of use (Chang & Wang, 2008; Moon & Kim, 2001). EE (i.e. ease of use), a potentially important perceived characteristic of information technologies, may influence the flow experience. Csikszentmihalyi and Csikszentmihalyi (1992) argued that the feasibility of performing an activity for a given individual facilitates flow. Thus, we assume that flow will be better for individuals that use robot technologies that are easier to use. In previous research, EE has been related to the perceived enjoyment of interacting with computer systems and to the flow experience while interacting with computers (Davis, 1989). Generally, people experience more pleasure when using a technology that requires less effort. Ease of use also facilitates concentration (Zhou, 2011). Therefore, EE is important to user concentration. Thus, we hypothesize that:

H3c: EE is positively associated with concentration while learning via robot-assisted learning systems.

2.4. Human likeness

2.4.1. Para-social relationships

The term "PSR" is a socio-relational term originally used in mass media research. It is defined as an emotional affinity between people and media characters resembling that experienced during a face-to-face relationship (Horton & Richard Wohl, 1956). Previous studies have focused on PSRs such as that between viewers and newscasters or actors and characters in television dramas, soap operas, or animated programs. Recently, studies have examined PSRs between users and their computer devices such as smart phones and embedded software such as mobile applications (Lee & Kwon, 2013). PSRs do not develop uniformly. Horton and Wohl (Horton & Richard Wohl, 1956) suggested that PSRs may be established because people tend to relate to and feel a familiarity with characters in mass media. Levy (1979) analyzed PSRs between newscasters and television viewers, showing that emotional bonds are key to the building of these relationships. In addition, perceived realism and affinity are main requirements for the development of PSRs (Rubin et al., 1985).

In previous studies in the field of educational psychology, the teacher-student relationship was found to affect student performance in terms of academic achievement and establishment of learning motivation (Davis, 2003; Howes, Hamilton, & Matheson, 1994; Pianta, Steinberg, & Rollins, 1995). Generally, affective relationships between students and teachers increase learning performance (Davis, 2003; Howes et al., 1994; Pianta et al., 1995). In self-system theories of motivation, warm and open relationships have been shown to foster student motivation for learning and to encourage positive task behaviors (Ames, 1992; Roorda, Koomen, Spilt, & Oort, 2011).

In the robot-assisted learning context, therefore, learner perception of the robotlearner relationship may also be relevant to adoption of robot-assisted learning. A positive PSR between the robot and the learner may result in better learning performance than for learners without a positive PSR. Hence, we hypothesize that:

H4a: The PSR between the user and the robot is positively associated with PE while using robot-assisted learning systems.

In addition, a PSR with the robot may affect the learner's concentration. A PSR is more than just an acquaintance (Koenig & Lessan, 1985). Such a relationship entails emotional attachment to the object of interest, in this case, the information system. In previous studies of PSRs, emotional attachment was identified as an important antecedent or dependent factor. Soukup (2006) mentioned that PSRs involve emotional attachment between fans and celebrities. In a study of users of educational games, Hsu, Wen, and Wu (2009) found that the commitment of players to the game was based on their avatars. The results of these studies imply that PSRs with information systems require a certain degree of concentration. Thus, we believe that in robot-assisted learning systems, which are a subset of information systems, the situation will be the same. As Lee and Kwon (2013) stated in their study on mobile device adoption, factors such as PSRs must be considered in assessing the potential of information technologies in terms of user satisfaction, post-adoption usage, and overall success.

The association of AI with PSRs and concentration is also supported by adoption theories related to information systems. Unlike enterprise-level information systems, which focus on undertaking business tasks effectively and efficiently (Delone & McLean, 2003), robot-assisted learning systems are individual systems that enable group-level communication between learner(s) and virtual teacher(s). According to the UTAUT2 theory, hedonic value is also important to system adoption. In addition, group-level communication is encouraged by socio-relational factors, which are critical to AI, as are flow-oriented factors such as concentration.

The role of the PSR as a socio-relational factor is also important in education theory, in which the student-teacher relationship is characterized and measured by the degree of closeness, conflict, and dependency. Here, closeness refers to the warmth and open communication that are characteristic of a given relationship. Conflict is observed in negative and coercive student-teacher interactions. Dependency refers to overly clingy student behavior. These three measures are closely related to student concentration. Learners tend to focus better when they have warm feelings for the teacher, and as a result, achievement is higher. It is reasonable to expect that the situation will be similar in the context of robot-assisted learning systems. Thus, we hypothesize that:

H4b: The PSR is positively associated with concentration while using robot-assisted learning systems.

2.4.2. Multimodal capability

A multimodal interface helps users to perceive a robot more as a substitute for a human teacher and less as a man-made device. The goals of MC are to maximize the robot's human likeness and cognitive and physical abilities, reduce the memory load for users in completing certain tasks, and minimize the cost of learning (Figure 2). Robot-assisted learning systems must be able to adapt to the abilities of different users, using the same terminology across modalities in order to ensure consistency of system interactions



Figure 2. Multimodal capabilities of the robot-assisted learning system examined in this study: touch, voice, and gesture.

(Reeves et al., 2004). A multimodal interface may minimize the effort required to operate learning systems, thus enhancing learning performance. Although multimodal interfaces have been shown to increase the user's perception of ease of use (Comai and Mazza, 2011; Dias et al., 2012; Stein, 1997), no empirical testing has been conducted in the context of robot-assisted learning. In order to rectify this situation, we hypothesize that:

H5a: MC is positively associated with EE while using robot-assisted learning systems.

A multimodal interface can also improve the PSR between the learner and the teaching robot. This notion can be understood in the context of the principle of the uncanny valley (Jentsch, 1906). Tinwell et al. (2011) described the uncanny valley as "a mental state where one cannot distinguish between what is real or unreal and which objects are alive or dead". Exploring this principle, studies have affirmed the positive relationship between perceived human likeness and perceived familiarity. Thus, feelings of intimacy toward a robot or other virtual characters are more positive, the more they resemble humans (Tinwell et al. 2011). According to PSR theory, human likeness enhances the PSR between users and virtual characters. In this study on robot-assisted learning involving humanoid robots, we assume that the more human-like the response provided by the robot, the stronger the PSR. Thus, we hypothesize that:

H5b: MC is positively associated with the PSR while using robot-assisted learning systems.

2.4.3. Media richness

MR was defined by Sheer and Chen (2004, p. 77) as follows:

the degree of richness measured by the quantity and quality of four attributes: a) the availability of instant feedback, b) the use of multiple cues such as voice inflection, body gestures and graphic symbols, c) the use of natural languages, and d) the personal focus of the medium.

According to flow theory, MR is the capacity to process rich information (Daft & Lengel, 1986). It has also been associated with user concentration and usage intention (Liu et al., 2009). Moreover, in e-learning system research, it is considered as an important factor



Figure 3. Media richness in the robot-assisted learning system examined in this study: a combination of screen display, speech, sound effects, color, light, and gestures.

affecting learning performance (Barra, Aguirre Herrera, Pastor Caño, & Quemada Vives, 2014; Ferretti, Mirri, Muratori, Roccetti, & Salomoni, 2008).

However, research based on conventional MR theory has only considered the type of content (e.g. text, audio, video, or a combination of these). For newer e-learning technologies such as robot-assisted learning (especially learning systems in which humanoid robots are used), MR must include representational richness due to the human representations characteristic of humanoid robots (e.g. speech synthesis, motions, and gestures; see Figure 3). Greater MR may facilitate learner understanding of the message conveyed by the robot-assisted learning system. Thus, we hypothesize that:

H5c: MR is positively associated with EE while using robot-assisted learning systems.

Additionally, according to MR theory, face-to-face interaction is richest because it has the capacity for immediate feedback and involves use of multiple cues and natural language, while plain text is the least rich mode of interaction (Daft & Lengel, 1986; Sheer & Chen, 2004). Face-to-face interaction is one of the essential characteristics of humanoid robots (Han & Kim, 2009; Hwang et al., 2008; Jahng, Jain, & Ramamurthy, 2006). Humanoid robots in robot-assisted learning systems offer stronger face-to-face interaction using non-verbal and verbal cues such as voice inflection, body gestures, directness, and instant feedback than other types of robots and traditional e-learning systems. Hence, we postulate that the more human-like the robot is, the higher the perception of MR will be. MR increases the learner's perception that devices such as robot-assisted learning systems are human-like, which facilitates formation of PSRs, according to PSR theory (Lee & Kwon, 2013; Levy, 1979). Thus, we hypothesize that:

H5d: MR is positively associated with development of PSRs between users and robot-assisted learning systems.

3. Methodology

3.1. Participants and data collection

Before the main survey was conducted, a pilot test including data from 50 respondents was performed to validate the measurement instrument and to reduce potential ambiguity in

the wording of items, questionnaire format, and instrument length. The purpose of this pilot test was to remove potential concerns about common method bias due to the use of a field survey technique. We found preliminary evidence that the scales were reliable and valid. These 50 participants were not included in the main survey.

The main survey was conducted over a period of two weeks. The questionnaire began with an opening statement about the purpose of this study and a paragraph that explained the meaning of robot-assisted learning. After reading these introductions, the parents of elementary school-aged child participants provided demographic information. The parents carefully observed a robot-assisted learning case that demonstrated how the functionalities of the robot-assisted learning system are used (see Figure 4). Finally, the parents responded to questions about their opinions of the system.

In this experiment, we used the DARwIn-op robot. The robot occupies the role of an adviser who helps in learning of the multiplication table. The learning software was designed for a human-robot interaction service. In the experiment, the robot asked the child multiplication questions and then calculated the number of correct answers. If the score was not satisfactory or the child hesitated to answer the questions, the robot adjusted the level of difficulty autonomously.

In this study, we surveyed the parents of the participating elementary school-aged children because parents have the purchasing power in most households. In our study, participating parents had great interest in robot-assisted learning systems for their children. For manufacturers of robots in e-learning systems, parents are their main customers. Therefore, it is important to determine which factors affect these customers' intention to purchase. Additionally, children's responses were not included in our survey due to the possibility of low reliability.

We collected 490 valid responses. The descriptive statistics relating to subjects' profiles are summarized in Table 1. The items utilized in the survey are listed in Table 2.



Figure 4. Experiment with robot-assisted learning

Category	Demographic information	Number	Percentage	
Age group	30s	149	30.4	
5 5 .	40s	340	69.4	
	≥50	1	0.2	
Gender	Male	242	49.4	
	Female	248	50.6	
Number of children (K–5th grade)	1	98	20.0	
	2	330	67.3	
	≥3	62	12.7	
Education	Senior high school	88	18.0	
	Bachelor's	347	70.8	
	Master's	44	9.0	
	Ph.D. or higher	11	2.2	
Occupation	Agriculture, forestry, or fisheries	1	0.2	
	Teacher or academic lecturer	9	1.8	
	Specialized job	26	5.3	
	Business career	17	3.5	
	Office job	197	40.2	
	Production, skill, or labor jobs	32	6.5	
	Service and sales	15	3.1	
	Self-employed	37	7.6	
	Freelancer	19	3.9	
	Full-time housewife	132	26.9	
	Other	5	1.0	

Table 1. Profiles of respondents (N = 490).

3.2. Measures

An initial model was developed that illustrates the relationships among the factors listed in Figure 1. A questionnaire was designed consisting of 29 items scored on a 7-point Likert scale and arranged into groups of 4 or 5 items addressing these factors.

Table 2. Survey items and sources.

_	_	No. of		
Theory	Construct	items	Operational definition	Reference
UTAUT2	PE	4	Degree to which robot-assisted learning is considered to improve learning achievement (based on the concept of performance expectancy)	Amended from Venkatesh et al. (2012)
	EE	4	Degree to which robot-assisted learning is considered by potential users as relatively easy to use and understand (based on performance expectancy)	Amended from Venkatesh et al. (2012)
	AI	4	Degree to which users intend to adopt the robot- assisted learning system or increase their use of it in the future	Amended from Venkatesh et al. (2012)
Para-social interaction theory	PSR	5	Degree of affective familiarity with the humanoid robot in the robot-assisted learning system	Amended from Lee and Kwon (2013)
Flow theory	CON	4	Degree to which users maintain exclusive, focused attention on robot-assisted learning activity	Amended from Liu et al. (2009), Koufaris (2002)
Media richness theory	MR	4	Degree of richness with which the robot is considered to express instruction when communicating with users	Amended from Jahng et al. (2006)
Human-computer interaction theory	МС	4	Degree to which users are aware of the natural interface method between themselves and the robot	Created for this study

Note: MC: multimodal capability; MR: media richness; PSR: para-social relationship; PE: performance expectancy; EE: effort expectancy; CON: concentration; AI: adoption intention.

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Using the definitions of the constructs outlined in Table 2, we derived the survey items used to measure the variables in the research model from prior research. The scales for the constructs utilized in this study (i.e. PE, EE, AI, coefficient of concentration (CON), PSR, and MR) were adopted from the UTAUT2 (Venkatesh et al., 2003), flow theory (Liu et al., 2009), PSR theory (Lee & Kwon, 2013), and MR theory (Jahng et al., 2006).

The concepts of MR and MC were extracted from the unique characteristics of robot-assisted learning via ubiquitous sensor networks in educational fields. A 7-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (7) was used to measure responses. PSR was measured using five items adopted from the scale proposed by Rubin and Perse (1987) and Sundar (2004). CON was measured using four items adopted from the scale proposed by Liu et al. (2009). PE, EE, and AI were measured using four items each adopted from the scale proposed by Venkatesh et al. (2012).

3.3. Assessing reliability and validity

To ensure the discriminant and convergent validity of the sample data set, the constructs were tested using exploratory factor analysis. Conventionally, a Cronbach's α coefficient between 0.870 and 0.965 indicates adequate reliability. In the reliability analysis for this study, the Cronbach's α coefficient of CON was 0.965. All dimensions exceeded 0.800, meaning that the questionnaire dimensions were highly homogenous, reliable, and reflective of the study's structural dimensions. The reliability coefficients are displayed in Table 3. To assess common method bias, Harman's single-factor test was conducted (Ong & Lai, 2006). All variables were included in an exploratory factor analysis and the first factor accounted for less than 50% of the variance, indicating that common method bias is not of great concern in this study.

Convergent validity was assessed according to the reliability of the items, average variance extracted (AVE) values, and factor analysis results. Item factor loadings and squared multiple correlations from the confirmatory factor analysis are shown in Table 3. Regarding internal consistency (reliability), composite reliability scores for every construct (ranging from 0.914 to 0.975, as shown in Table 3) were well above 0.70. AVE measures the amount of variance that a construct captures from its indicators relative to the amount due to measurement error. The overall AVE score was calculated from the square roots of the AVE scores listed in Table 3. AVE scores for every construct, ranging from 0.794 to 0.906, satisfied the necessary requirements. Barclay, Higgins, and Thompson (1995) suggested that item loadings for all constructs should exceed 0.70. In this study, the loadings of each item met this criterion (Table 3).

Discriminant validity was assessed by examining the relationship between correlations among constructs and the square roots of AVE values (Fornell & Larcker, 1981). The square roots of the AVE values should be greater than the correlations among the constructs, indicating that more variance is shared between the construct and its indicators than with other constructs. Table 3 shows that the square roots of all the AVE values (i. e. the numbers on the diagonal) were greater than the correlations among constructs (i. e. the off-diagonal numbers), indicating that the discriminant validity of all constructs was satisfactory.

Constructs	ltems	Factor loadings	<i>T</i> -value	CR	CA	CON	EE	AI	MC	PE	PSR	MR
CON	CON1	0.937	45.750	0.975	0.965	0.952						
	CON2	0.961	99.689									
	CON3	0.958	89.220									
	CON4	0.950	67.661									
EE	EE1	0.922	43.814	0.964	0.950	0.385	0.933					
	EE2	0.939	52.307									
	EE3	0.930	47.141									
	EE4	0.941	61.563									
AI	AI1	0.897	32.485	0.969	0.957	0.680	0.348	0.942				
	AI2	0.961	100.494									
	AI3	0.961	96.889									
	Al4	0.947	78.132									
MC	MC1	0.913	44.472	0.948	0.927	0.647	0.518	0.619	0.906			
	MC2	0.924	62.526									
	MC3	0.907	41.794									
	MC4	0.878	25.331									
PE	PE1	0.931	57.454	0.970	0.959	0.610	0.391	0.750	0.552	0.943		
	PE2	0.956	89.201									
	PE3	0.947	67.223									
	PE4	0.939	60.795									
PSR	PSR1	0.896	22.947	0.948	0.927	0.762	0.357	0.701	0.678	0.641	0.906	
	PSR2	0.918	37.894									
	PSR3	0.917	42.609									
	PSR5	0.893	36.096									
MR	MR1	0.885	32.596	0.914	0.870	0.663	0.524	0.664	0.723	0.609	0.668	0.853
	MR2	0.866	23.375									
	MR3	0.920	37.490									

Table 3. Reliability and discriminant and convergent validity.

Notes: The recommended levels for these statistics are as follows: AVE > 0.50, composite reliability (CR) > 0.70, Cronbach's α (CA) > 0.70. Other abbreviations are in Table 2.

4. Results of path analysis

The proposed model was tested using structural equation modeling (SEM) and partial least squares (PLS) analysis (Ringle, Wende, & Will, 2005) according to the methods described by Teo, Wei, and Benbasat (2003). SEM is a statistical analysis technique designed to test conceptual or theoretical constructs. SEM consists of a set of linear equations that simultaneously test two or more relationships among directly observable and/or unnamed latent variables. This technique has become extremely popular for data analysis in education, psychology, business, and other disciplines (Finney & DiStefano, 2006). By contrast, PLS is a form of SEM. In many recent studies in behavioral research, PLS is widely used because this method requires no model to explain the covariance of all indicators, and because model latent variables can be tested under non-normal conditions (Püschel, Afonso Mazzon, Mauro, & Hernandez, 2010). In this paper, the data were analyzed using the PLS software (Smart-PLS version 2.0).

Table 4 and Figure 5 present the properties of the causal paths, including standardized path coefficients, t-statistics, and explained variance for each equation in the hypothesized model. In the PLS analysis, examining the R^2 scores of endogenous variables allows assessment of the utility of the variables, and examining the structural paths facilitates assessment of the explanatory power of the structural model.

First, affective factors (including concentration) were investigated in terms of flow theory. The results indicated that concentration was positively and significantly associated with robot-assisted learning AI ($\beta = 0.354$, p < .01). The concentration on robot-assisted learning was also positively influenced by EE ($\beta = 0.133$, p < .10). Thus, H1 and H3c were supported.

Second, cognitive factors from the TAM (including PE and EE) were investigated. The results indicated that PE was positively and significantly associated with robot-assisted learning AI ($\beta = 0.531$, p < .01). However, the relationship between EE and robot-assisted learning AI was not significant. PE related to robot-assisted learning was positively influenced by EE ($\beta = 0.188$, p < .10) Thus, H2 and H3b were supported, but H3a was not supported.

Third, relationships between the dimensions derived from para-social interaction theory (including PSR) and the TAM and flow theory dimensions were analyzed. The

Hypoth	nesized paths	Path coefficients	T-value	Results of analysis	
H1	CON while learning is positively associated with Al.	0.534***	3.139	Supported	
H2	PE is positively associated with AI.	0.531***	4.839	Supported	
H3a	EE is positively associated with AI.	-0.008	0.112	N.S.	
H3b	EE is positively associated with PE.	0.188*	1.761	Supported	
H3c	EE is positively associated with CON while learning.	0.133*	1.838	Supported	
H4a	PSR is positively associated with PE.	0.580***	7.210	Supported	
H4b	PSR is positively associated with CON.	0.714***	11.047	Supported	
H5a	MC is positively associated with EE.	0.237*	1.927	Supported	
H5b	MC is positively associated with PSR.	0.472***	3.938	Supported	
H5c	MR is positively associated with EE.	0.402***	3.104	Supported	
H5d	MR is positively associated with PSR.	0.298**	2.462	Supported	

Table 4. Results of model effects.

***Significant at the .01 level.

**Significant at the .05 level.

*Significant at the .10 level.



Figure 5. Model testing results.Notes: MC: multimodal capability; MR: media richness; PSR: para-social relationship; PE: performance expectancy; EE: effort expectancy; CON: concentration; AI: adoption intention. *** p < .01. ** p < .05. * p < .10.

results showed that PE ($\beta = 0.580$, p < .01) and concentration ($\beta = 0.714$, p < .01) were positively influenced by the PSR. Thus, H4a and H4b were supported. In terms of the direct effects of factors, we found a greater impact of the PSR on the affective factor (i. e. CON) than on cognitive factors (i.e. PE and EE).

Fourth, we examined the relationships between interactivity dimensions (including MC), TAM dimensions (including EE), and para-social interaction theory dimensions (i.e. PSR). The results showed that both EE ($\beta = 0.237$, p < .10) toward learning using a robotic system and the PSR ($\beta = 0.472$, p < .01) were positively influenced by MC. Thus, H5a and H5b were supported.

Lastly, the relationships between the para-social interaction theory dimension (i.e. PSR), the TAM dimensions (i.e. PE and EE), and the flow theory dimension (i.e. concentration) were investigated. The results showed that both EE ($\beta = 0.402$, p < .01) toward learning using a robotic system and PSR ($\beta = 0.298$, p < .05) were positively affected by MR. Thus, H5c and H5d were supported.

5. Discussion and conclusion

5.1. Theoretical implications

In this study, a theoretical model of adoption of robot-assisted learning systems was developed and tested empirically. Robot-assisted learning has advanced recently due to developments in e-learning and robot technologies. However, though research has demonstrated the educational effectiveness of innovative e-learning methods (Hwang et al., 2008; Lee & Kwon, 2013), no empirical studies have been conducted on the adoption of innovative e-learning systems, especially robot-assisted learning systems. Research in this area is necessary in the fields of education and information technology. In this study, a robot-assisted learning prototype was utilized and survey data were collected from general users. The resulting data were empirically tested, and the test results were provided and analyzed. Second, in the proposed model, constructs derived from studies with a socio-relational perspective, namely the PSR, successfully illustrated the concept of human likeness and were integrated with those derived from studies based on conventional adoption theories. The socio-relational perspective was linked to para-social interaction theory to improve our understanding of the learner's psychological process in deciding to adopt robot-assisted learning systems. The significant effect of this process was verified through empirical analysis. With its MC and enhanced MR (i.e. voice synthesis and gestures), the resemblance to humans of humanoid-type robots was found to be significant to learners' perceptions of robot-assisted learning systems as educationally effective. This factor also had significant influence on user concentration. These results suggest that in developing new technologies involving robot technology, such as robot-assisted learning, the interaction of humans and humanoid robots must be considered.

Both cognitive and affective factors were found to affect intention to adopt robotassisted learning systems. PE and EE were tested as two major cognitive factors common to technology adaptation theories. In addition, the effect of one affective factor – concentration – on intention to adopt robot-assisted learning was examined based on flow theory. PE had the strongest direct impact on intention to adopt robotassisted learning. Second was concentration. However, no direct impact of EE was found. Thus, two factors, PE and concentration, explained 63.3% of the variance in intention to adopt robot-assisted learning in this study.

Finally, EE had an indirect influence on intention to adopt robot-assisted learning systems through PE and concentration. The direct effects of PE and concentration on intention to adopt robot-assisted learning were significant, although those of EE were not. However, the importance of EE was demonstrated by the fact that both cognitive and affective factors were identified as determinants of intention to adopt robot-assisted learning. In addition, the effect of EE on PE was consistent with the findings of previous technology adoption studies (Koufaris, 2002; Venkatesh et al., 2012).

5.2. Practical implications

In this empirical study, MC and MR in robots were found to have an important role in forming relationships between robots and learners. As explained earlier, MC and MR are important in creating a natural human–robot interface based on the robot's likeness to humans; these constructs are needed to facilitate usage of robot-assisted learning technologies. Research has found that robots that resemble human beings are more successful in providing educational content to students. The importance of human likeness was emphasized in this study, as shown by the significant effect of the PSR on PE and concentration. In practical terms, the adaptability of potential users may be increased by improving the level of human likeness in robots to facilitate mutual interaction between users and robots in the context of robot-assisted learning. Hinds et al. (2004) also claimed that humanoid robots provide a more natural interface than more mechanistic robots. Thus, directives for development of robot-assisted learning should include development of robots to resemble humans as much as possible in order to increase the practical adaptability of this form of learning.

In this study, the important role of educational robotic learning systems was verified; robot-assisted learning was effective in increasing the level of learning, PE and EE, and degree of concentration of users. Robots used for robot-assisted learning may occupy three roles: they may help users meet learning objectives, assist users in learning, and act as learning tools. In these roles, the interaction between robots and learners is most important when robots are used as learning assistants and learning tools. The role of the teacher is extremely important, but any teacher has limited ability to interact with all students in a classroom. Thus, educational robots may be useful as teaching assistants.

Lastly, concentration was identified as a significant affective factor in terms of intention to adopt robot-assisted learning. This result suggests that robot-assisted learning can be made more salable by adding "fun factors" to enhance performance and other features to attract and retain attention of users. As discussed above, robot-assisted learning is a new way to learn among many possible ways of learning, and it has not yet matured technologically. Market formation is still in the initial stage. This new study on adoptability of robot-assisted learning has value in its evaluation of the effects of various factors on intention to adopt robot-assisted learning, providing strategic implications for developers about which characteristics to focus on and what requires supplementation from a practical perspective.

5.3. Limitations

This study of robot-assisted learning involves a specific type of humanoid robot. However, development of humanoid robots has not yet reached the level at which it may be equated with an actual human being as an information medium offering learning content due to technological limitations in judgment and expression. In addition, the robot-assisted learning system included in this study was only a prototype of a full learning model. Accordingly, the results of this study should not be generalized to all robots used in educational settings and all academic fields. Nonetheless, this study has value as the first empirical study identifying factors related to adoption of robot-assisted learning. More in-depth studies can be carried out in the future including robots resembling humans to a greater extent and in different settings and fields.

Other facilitating conditions such as list price or usage location may also be important factors affecting robot adoption. However, these facilitating conditions in general affect the actual purchase, not intention to adopt. Moreover, price level and usage location are already well-known factors affecting adoption behavior. Because we did not include these factors in our research model, future research may want to examine them in the context of the robot-assisted learning.

Moreover, the methodology used in this study has some limitations because the constructs in our model (PE, EE, PSR, and CON) were measured indirectly by parents. In the future, we plan to perform a confirmatory study by directly collecting the responses of the children to determine if their intention to adopt this technology is consistent with that of their parents.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work is supported by the National Strategic R&D Program for Industrial Technology [10041659] and funded by the Ministry of Trade, Industry, and Energy (MOTIE).

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