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My Health Advisor is a Robot: Understanding Intentions to Adopt a Robotic Health Advisor

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ABSTRACT

Robots and artificial intelligence (AI) have seen increased adoption in healthcare. These health technologies have the capability of providing tailored messages and feedback to each individual. Thus, a robot can potentially serve as a personal health advisor, particularly for health issues that could be benefited through regular guidance and instructions. However, there is a limited understanding of how people might respond to the idea that their health advisor could be a robot. Thus, the present study employs the technology acceptance model (TAM) to examine intentions to adopt a robotic health advisor. Findings demonstrate that perceived ease of communication with and perceived usefulness of a robotic health advisor positively predict favorable attitudes toward a robotic health advisor, which subsequently leads to strong intentions to adopt it. The present investigation also finds that perceived usefulness of a robotic health advisor directly leads to an individual's intentions to adopt it. Overall, the present study provides important implications for perceptions of a robotic health advisor.

KEYWORDS

Robotic advisor; human-machine communication; social robots; artificial intelligence; health technology

1. Introduction

Artificial intelligence (AI) is an intelligent system that continuously adapts to its surrounding environment to complete tasks and achieve goals (Russell & Norvig, 2016). AI technologies can appear as a software-based operating system in a virtual environment, such as chatbots, or embedded in hardware devices, such as robots (Renda, 2019). These technologies are increasingly being used in healthcare. In particular, healthcare robots are considered one of the top 10 important areas for robotic technologies in the next 10 years (Yang et al., 2018).

Various categories of healthcare robots exist, such as nurse robots, telemedicine robots, hospital serving robots, surgical robots, radiologist robots, and rehabilitation robots (Khan et al., 2020). In general, these healthcare robots are primarily designed to improve people's health and facilitate healthy lifestyles (Davenport & Kalakota, 2019). For example, surgical robots such as ROBODOC, the first surgical robot that received FDA approval (Oborn et al., 2011), and The Da Vinci surgical system (Olaronke et al., 2017), are common types of healthcare robots. Another type of healthcare robots is a socially assistive robot (SAR), which is a social robot that is capable of engaging in social interactions with humans (Abdi et al., 2018). SARs have been used in healthcare settings in various ways, such as assisting in physical therapy sessions (Kyrarini et al., 2021) and assisting patients in managing their physical and psychological well-being (Scoglio et al., 2019). There are also healthcare robots that aid disabled and/or cognitively impaired individuals to live an independent life (Tejima, 2001) and motivate people to exercise and lose weight (Kidd & Breazeal, 2005).

Healthcare robots also have the capacity to substantially contribute to health education or provide educational information for improving health. For example, robots used in psychological management are equipped with visual and audio technologies to not only assist patients but to elucidate upon their conditions and assist in constructing healthier psychological schemas (Scoglio et al., 2019). Also, Blanson Henkemans et al. (2013) observed that children with Type 1 diabetes obtained increased knowledge of their condition after interacting with social robots. The notable success of adopting these healthcare robots has been reported in a variety of health contexts, including nursing care (Hamstra, 2018), complex surgical procedures (Mayo Clinic, 2021), and assisting senior living residents (Kourtney, 2021). Overall, research reports that healthcare robots contribute to enhanced patient care (Ruiz-del-Solar et al., 2021).

However, while much attention focuses on the use of healthcare robots in a hospital setting (e.g., Mayo Clinic, 2021; Scoglio et al., 2019) and in living communities like nursing homes (e.g., Abdi et al., 2018; Kourtney, 2021), relatively little information is documented regarding healthcare robots designed to help individuals in personal settings or

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circumstances. Thus, there is a need to understand healthcare robots as personal health advisors and how people perceive them. To address this research gap and need, the present study explores people's perceptions of a robotic health advisor and their intentions to adopt a robotic health advisor through the framework of the technology acceptance model (TAM).

2. Literature review

2.1. Robots as a personal health advisor

Although the term, "robotic health advisor," is not widely used, previous literature addresses the personalized coaching or advising aspect of healthcare robots. In particular, Bickmore et al. (2005) developed a virtual agent that serves as an exercise coach that provides educational information about exercise, asks about the user's daily activity levels, records progress, and provides feedback. Similarly, Kidd and Breazeal (2008) developed a table-top robot that served as a weight-loss coach. The robot's primary roles include tracking user progress and helping the user with weight-loss. In their study, users reported that interacting with a robot was more helpful in tracking exercise behavior and calorie consumption than other methods such as using a computer or a traditional paper log.

Research has examined which features of robots could maximize health benefits for the users. Fasola and Matarić (2013) investigated how embodiment of robots influences exercise experiences. The study found that people evaluate a physically embodied robot to be more enjoyable, useful, and helpful compared to a virtually embodied robot that appears as a computer simulation of the same robot. In another study, Powers and Kiesler (2006) examined the effects of a robot's voice and physical appearance on willingness to follow the robot's health advice. The study found that a robot with a male's voice (compared to a female's voice) increased perceptions of the robot's knowledge, which naturally fosters greater intentions to follow the robot's advice.

2.3. AI robotic health advisor

Considering that one of the features of an effective advisor is to provide personalized or tailored advice and suggestions, robotic health advisors would be particularly effective when combined with AI systems. AI demonstrates intelligence by analyzing input from the external environment and taking actions to pursue specific goals. AI systems can manifest as software that operate in virtual environments like chatbots or can be embedded in hardware devices such as robots (Renda, 2019). In this regard, AI robotic health advisors can provide substantial benefits.

In fact, unique features of AI can provide promising ways to maximize the health benefits received from AI-based robotic health advisors. First, a robotic health advisor can obtain patients' healthcare data in an efficient manner (Long et al., 2017) and provide personalized feedback (Wilk et al., 2017). That is, based on data collected from users, AI can automatically identify the user's abilities, preferences, and motivations by analyzing their behavioral patterns and diets and provide tailored information according to their preference and motivation (Wilk et al., 2017). Also, depending on users' health literacy, personality, and communication styles (Song et al., 2020), a robotic health advisor can provide tailored advice to each individual.

The aforementioned capabilities of AI are well documented in empirical studies. Fitzpatrick et al. (2017) investigated the effects of *Woebot*, a conversational virtual AI agent designed to help address mental health concerns among college students with anxiety and depression. After communicating with *Woebot* for a few weeks, the students reported positive changes about themselves, such as reduced symptoms of depression and anxiety. Further, Fitzpatrick et al. suggest that *Woebot's* capability to provide tailored messages helps the user set goals and stay accountable. Thus, this study's findings showcase how an AI robotic health advisor can be helpful in addressing personal health issues.

Second, an AI robotic health advisor can be particularly helpful for those who feel uncomfortable sharing sensitive information with a human healthcare provider. People often withhold sensitive information from their doctors for fear of negative judgment and embarrassment (Levy et al., 2018). However, people are more willing to disclose private or personal information to robots because they perceive robots to be unbiased (Aroyo et al., 2018). Thus, people would be more likely to perceive that robots are not judgmental and that their task is to deliver their message without any hidden agenda (Hoorn & Winter, 2018). Considering that people tend to treat machine agents as social beings (Reeves & Nass, 1996), it is logical to assume that people would naturally engage in casual conversations with robots. These features ultimately heighten the perceived credibility and the acceptance of a message from the robots to the users (Hoorn & Winter, 2018), which would make a robotic health advisor's role effective.

Further, humans' expectation that machines could perform better than humans in some areas (Cohen et al., 1998; Lee & See, 2004) may maximize the benefits of adopting AI robotic health advisors. Humans tend to possess automation bias toward machines, which suggest that humans hold positive attributes toward capabilities of automatic systems or machines (Sundar, 2008). Thus, people are more likely to think that suggestions by computers or machines are more objective and reasonable than suggestions by humans (Dijkstra et al., 1998), which may lead to increased compliance of the suggestions that are tailored to them.

2.4. Study context: AI robotic health advisor for weight management

Considering the varying health-related concerns people may experience, the present study focuses on one particular aspect: weight problems. Statistics report alarming signals for the global epidemic of obesity. Obesity rates have tripled since 1975 (World Health Organization [WHO], 2020a), and approximately 2.8 million people die each year from obesity across the globe (WHO, 2020b). In the United States, 42.5% of adults aged 20 and over are categorized as obese, and 73.6% of adults aged 20 and over are overweight (CDC, 2020). These reports indicate that only less than one-third of the U.S. population maintains a healthy weight. Considering that being overweight or obese are associated with other health problems, such as cancer, cardiovascular disease, and depression (WHO, 2016), combating weight problems is a critical issue.

To mitigate the negative effects of being overweight or obese, some individuals may receive counseling from healthcare providers. However, most individuals who are overweight or obese do not receive counseling from their healthcare provider regarding their weight issues, and only about half of those who received counseling act on the advice they received (Greaney, 2020). Some reasons explaining why healthcare providers do not offer counseling include time constraints during the visit, limited training on counseling, and low self-efficacy to perform counseling (Block et al., 2003; Kolasa & Rickett, 2010). Further, for various reasons and demands, medical schools in the U.S. do not adequately prioritize obesity issues in the medical education curricula (Butsch et al., 2020). Thus, there is a lack of human resources to help individuals who need advice and guidance to maintain a healthy lifestyle.

One solution to address the limited capabilities of humans might be to adopt robotic health advisors. As mentioned earlier, the AI robotic health advisor can offer tailored information that is specific to each individual. In this regard, an AI robotic health advisor can address people's needs to receive advice for promoting and maintaining a healthy diet and lifestyle. However, little is known about whether people would consider using a robotic health advisor. Therefore, the present study explores perceptions of a robotic health advisor and intentions to adopt a robotic health advisor through the framework of the technology acceptance model (TAM).

2.5. Technology acceptance model

The technology acceptance model (TAM) explains how individuals accept and adopt a new technology (Davis, 1989; Davis et al., 1989). In particular, the TAM predicts that the ultimate adoption of a new technology is guided by one's intentions to use a particular technology. Two key fundamental concepts of the TAM explain the adoption of technologies, perceived ease of use and perceived usefulness.

Perceived ease of use refers to the degree an individual views a technology to be simple to interact with or manage (Davis, 1989), whereas *perceived usefulness* refers to the degree an individual views how practical or capable a new technology is to perform a given task. According to Abdullah and Ward (2016), perceived ease of use directly affects the perceived usefulness of a technology. Further, perceived usefulness is a fundamental mechanism of technological adoption as it is directly associated with an individual's intentions to adopt a new technology (Davis et al., 1989). Both perceived ease of use and perceived usefulness positively influence an individual's attitudes toward a particular technology. Subsequently, positive attitudes lead to an individual's intention to use or adopt the technology, which consequently lead to adoption of the technology (Davis et al., 1989).

Researchers have applied the TAM to better understand adoption of AI and robots. For example, Xu and Wang (2021) examined how law officials perceived a developmental robotic law clerk. The study ultimately found that perceived usefulness was positively related to intentions to adopt the robotic law clerks. In an education context, Kim et al. (2020) examined college students' intentions to adopt an AI-based education. This study found that perceived ease of communication with and perceived usefulness of an AI teaching assistant fostered favorable attitudes toward the AI teaching assistant, which consequently predicted increased behavioral intentions to adopt an AI-based education.

More germane to the present study's context, the TAM has been also used in the healthcare context. Saadatzi et al. (2020) investigated responses to robotic nurse assistants, which are assistive robots designed for escorting patient, deliveries, patient observation, and condition feedback, and found that perceived ease of using the robotic nurse assistant is an important factor for adoption. Moreover, de Graaf et al. (2015) examined elderly individuals' perceptions of a robotic assistant deployed in their homes and found that ease of use is positively related to the adoption of the robotic health assistant.

To sum, considering the rapid advancements of new technologies, it is possible that a robotic health advisor might become more available and accessible in healthcare in the coming future. In this regard, the present study examines how people would perceive a robotic health advisor and how their perceptions would lead them to consider adopting the technology based on the TAM framework, specifically in the context of weight management. Given that the robotic health advisor is considered as a digital interlocular rather than a mere technology tool or algorithm (Spence, 2019) in this study, perceived ease of use is referred to as perceived ease of communication. See Figure 1.

H1: Perceived ease of communication with a robotic health advisor positively predicts perceived usefulness of a robotic health advisor.

H2a-b: (a) Perceived usefulness of a robotic health advisor and (b) perceived ease of communication with a robotic health advisor positively predicts favorable attitudes toward a robotic health advisor.

H3: Favorable attitudes toward a robotic health advisor positively predicts greater intentions to adopt a robotic health advisor.

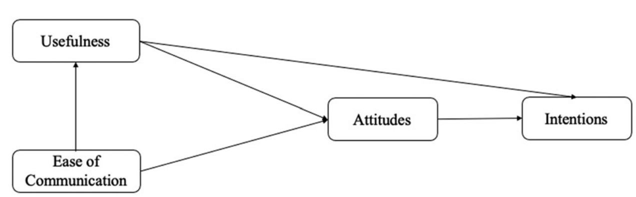

Figure 1. Hypothesized Research Model.

H4: Perceived usefulness of a robotic health advisor positively predicts greater intentions to adopt a robotic health advisor.

3. Methods

3.1. Materials

To expose participants to the idea of a robotic health advisor, the study used short video clips. These clips were edited from a documentary, *The Robot Will See You Now*, which was released in November in 2017 in the United Kingdom. The main storyline of the documentary features an AI robot, "Jess," who offers counseling and advice to people on various topics ranging from physical health to social and relational health. The documentary shows a series of recorded interactions between the robot, Jess, and people in a comfortable home setting.

For the purpose of this study, two short clips were edited from the documentary. These edited clips portrayed a description of a robotic personal health advisor (a personal assistance robot), who offers advice on an issue regarding weight management, and its interaction with humans. Specifically, the first clip included a brief introduction of the robotic health advisor, Jess. The clip showed a greeting from Jess and the features and capabilities of Jess, such as being able to access clients' data and giving advice to people regarding their problems. The introductory clip was approximately 1 minute and 10 seconds in length. The second clip showed a face-to-face interaction between Jess and a couple, Hayley and Ronny, which occurred at a home where Jess is located. The conversation topic was about Hayley's weight issue. In the clip, Jess asked Hayley a series of questions about her weight and eating habits and accessed Haley's health-related data to give advice and suggestions to help manage her weight. The clip was approximately 2 minutes and 10 seconds. The interaction reflected a real-life situation.

3.2. Procedure

Following approval from a university's Institutional Review Board (IRB), the lead author reached out to several instructors who agreed to provide this research participation opportunity to their undergraduate students. Instructors at the lead author's institution were invited to share this opportunity with their students. The lead author sent a recruitment message to the interested instructors, and they delivered the message to their students (a pool of potential participants). In order to participate in this present study, individuals must have been at least 18 years old at the time of completing the study.

Interested and eligible students were invited to visit the link that connects to the study participation. After acknowledging the informed consent, participants were instructed that they would watch two short video clips as part of the study. A timer was set for each clip, which did not allow participants to proceed without watching the clips in full. Then, participants responded to a series of questions about their perceptions of a robotic health advisor, which was included in the content they watched in the clips. The study was conducted fully online; that is, participants watched the videos and completed the survey questionnaire in the place of their choosing. Participation was voluntary, and all participants received extra credit. Confidentiality was guaranteed.

3.3. Data cleaning and sample

Initially, 238 individuals responded to the study's recruitment message. To maximize the quality of the data, data cleaning processes were conducted. First, responses from 12 individuals were removed because they failed the attention check question, which asked about the name of the robot featured on the clips. Second, responses from four individuals were eliminated to avoid potential biases about the content because they reported that they had previously seen the original documentary. Lastly, responses from one individual were removed because they indicated that they have participated in this study more than once; thus, the response from their second attempt was removed.

The final sample consisted of 221 participants. The sample included more females ($n = 128$: 57.9%) than males ($n = 93$: 42.1%). The average age was 20.11 years ($SD = 3.05$). Participants identified as White/Caucasian ($n = 104$: 47.1%), followed by Latine or Hispanic ($n = 62$: 28.1%), Black/African American ($n = 30$: 13.6%), Asian ($n = 20$: 9.0%), and other ethnic groups ($n = 5$: 2.3%). The majority of the participants ($n = 190$: 86%) reported that they have not interacted with a robot before.

3.4. Measures

Several questions were asked to evaluate perceptions of Jess, a robotic health advisor. *Perceived usefulness of a robotic health advisor* (Cronbach's $\alpha = 0.93$; $M = 3.69$; $SD = 1.48$) was evaluated with four items (e.g., "A robot similar to Jess would be useful to me" and "… would enhance the quality of my life"). *Perceived ease of communication with a robotic health advisor* (Cronbach's $\alpha = 0.85$; $M = 4.40$; $SD = 1.23$) was assessed with four items (e.g., "I would find it easy to get a robot similar to Jess to respond to my request" and "I would find it easy to interact with a robot similar to Jess"). Responses for both scales were recorded on a 7-point Likert-type scale (e.g., 1 = *Strongly Disagree*, 7 = *Strongly Agree*). Items for both measures were adopted from Davis (1989).

Attitudes toward a robotic health advisor (Cronbach's $\alpha = 0.94$; $M = 4.38$; $SD = 1.43$) were assessed with five items (e.g., "*harmful – beneficial*" and "*unfavorable – favorable*"). Responses were obtained on a 7-point semantic differential scale. The measure was adopted from Davis (1993).

Intentions to adopt a robotic health advisor (Cronbach's $\alpha = 0.93$; $M = 3.88$; $SD = 1.63$) were measured with three items (e.g., "If a robot similar to Jess is available, I would consider using it" and "… I would be interested in adopting it."). Responses were recorded on a 7-point Likert-type scale (e.g., 1 = *Strongly Disagree*, 7 = *Strongly Agree*). The measure was adopted from Choi and Ji (2015). A complete set of measures is available here: https://osf.io/zxue2/?view_only=08f8546020134a79ab52e97ac1cf1dca.

4. Results

Prior to the hypothesis testing, control variables were considered. Prior research suggests that participants' sex and previous experiences with using technology could affect their attitudes toward technologies and intentions of future use (Johnson et al., 2004; Nass et al., 1995; Xu, 2019). Thus, sex (male or female) and previous experience with using robots (yes or no) were used as control variables (dichotomous variables) in the analysis.

To test the proposed hypotheses and overall model fit as guided by the TAM, structural equation modeling (SEM) was conducted using Mplus (Muthén & Muthén, 2015). According to Hu and Bentler (1999), a model has acceptable fit when the chi-square test (X^2) is non-significant, comparative fit index (*CFI*) is greater than 0.95, the root mean square error of approximation (*RMSEA)* is smaller than 0.06, and the standardized root mean of squared residual (*SRMR*) is smaller than 0.08. In the present study, controlling for participants' sex and previous experience using robots, the model demonstrated acceptable fit for the observed data, X^2 (1, $N = 219$) = 3.05, $p = 0.081$, $CFI = 0.995$, $RMSEA = 0.097$, $SRMR = 0.012$. The study's data reported that RMSEA was larger than the cutoff value proposed by Hu and Bentler (1999). However, the value of RMSEA smaller than 0.10 is still considered as fair fit (Hooper et al., 2008; MacCallum et al., 1996), and the decision of model fit is based on a set of multiple indices (e.g., Chi-Square, CFI, SRMR) and not just the RMSEA. Thus, the model presented goodness of fit.

Next, each path in the model was assessed to answer the proposed hypotheses. Regarding H1, perceived ease of communication with a robotic health advisor positively and significantly predicted perceived usefulness of a robotic health advisor ($B = 0.59$, $p < 0.001$). With regard to H2a-c, both perceived ease of communication with ($B = 0.26$, $p < 0.001$) and perceived usefulness of a robotic health advisor ($B = 0.59$, $p < 0.001$) positively and significantly predicted positive attitudes toward a robotic health advisor. Regarding H3, positive attitudes toward a robotic health advisor positively predicted greater intentions to use a robotic health advisor in the future ($B = 0.26$, $p < 0.001$). For H4, perceived usefulness of a robotic health advisor positively predicted intentions to adopt it when it is available ($B = 0.66$, $p < 0.001$). Overall, all proposed hypotheses were supported. The model with statistical information is reported in Figure 2.

5. Discussion

The present study investigated perceptions of and intentions to adopt a robotic health advisor based on the TAM framework. Findings demonstrate that perceived ease of communication with and perceived usefulness of a robotic health advisor positively predict favorable attitudes toward a robotic health advisor, which subsequently lead to greater intentions to adopt a robotic health advisor when it becomes available. Further, perceived usefulness of a robotic health advisor directly predicts intentions to adopt it. The following section explains primary findings, discusses implications and contributions, as well as limitations and future research directions.

5.1. Primary findings and implications within the TAM framework

The present study reveals meaningful findings. First, consistent with the TAM (Davis, 1989; Davis et al., 1989), the study's findings demonstrate that perceived ease of use (referred to as perceived ease of communication in the present study) and perceived usefulness of a robotic health advisor lead to developing positive attitudes toward a robotic health advisor. Considering that attitudes are key to technology adoption (Davis, 1989), these results suggest the need to find ways to foster those perceptions among potential technology adopters. In fact, Venkatesh and Davis (1996) found that perceived ease of use can be developed through one's perceived self-efficacy. According to social cognitive theory (Bandura, 1997), self-efficacy can be enhanced by several factors, such as direct experiences, encouragement from others, and observing/modeling others' behaviors. As such, the present study provides some recommendations to apply theory-driven suggestions in the study's context. For example, one could provide a hands-on tutorial session that consists of interacting with a robotic health advisor, receiving supportive feedback from the robotic health advisor, and viewing others communicating with a robotic health advisor. This exposure with a robotic health advisor might help individuals develop a sense of self-efficacy of using it, which would help increase perceived ease of use. A series of empirical research studies would help verify these suggestions or conjectures.

Of particular importance, the present study reveals that perceived usefulness of a robotic health advisor positively and directly predicts intentions to adopt a robotic health advisor when it becomes available. Along with other findings of tested hypotheses in the present study, this result is consistent with the core prediction of the TAM (Davis, 1989). That is, while both perceived ease of use and perceived usefulness are fundamental constructs that facilitate one's adoption of a technology, the TAM particularly highlights the importance of perceived usefulness (Davis, 1989; Venkatesh & Davis, 2000). This prediction is also well evidenced in empirical studies (e.g., Kim et al., 2020). For example, research reports that when people perceive the usefulness and capabilities of a home healthcare technology, they are more likely to adopt the technology (Alaiad & Zhou, 2014).

This association between perceived usefulness and intentions to adopt suggests the need to create effective strategies for fostering perceived usefulness of a technology.

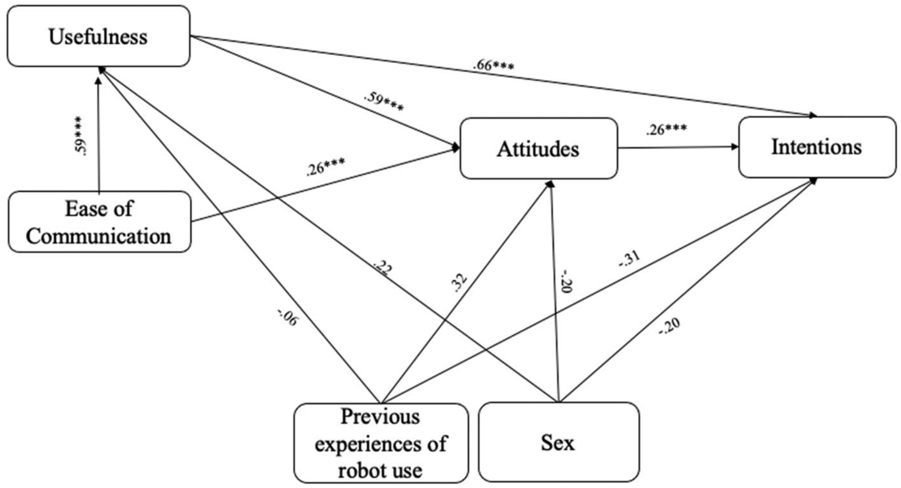

Figure 2. Results of SEM
Note. Model fit: X^2 (1) = 3.05, $p = 0.08$, CFI = 0.995, RMSEA = 0.097, SRMR = 0.012. Numbers are unstandardized coefficients.
*** $p < 0.001$.

Suggestions can be developed based on the extant literature. For example, social influence, such as subjective norms, can be a good approach to assess these relationships from, as individuals may be more likely to adopt a technology when they perceive that others who are important to them consider the technology as useful and important (Venkatesh & Davis, 2000). Focusing on functional features of a robot could also be an effective strategy to foster perceived usefulness as evidenced by the extant literature (e.g., Kim et al., 2021). For example, healthcare workers perceive healthcare robots as useful when they perform task-related behaviors, such as lifting and diagnostics (Turja et al., 2018). Considering that a robotic health advisor is a new concept that has not been widely discussed, it seems particularly important to inform people about potential usefulness and practical values of this technology. Thus, the present study suggests the need to find ways to foster greater perceived usefulness of a robotic health advisor.

Overall, the study's findings enhance our understanding of various factors that contribute to the acceptance and potential adoption of robotic health advisors by highlighting the utility of the TAM. Since its introduction into the field (Davis, 1989; Davis et al., 1989), the TAM has been applied in a wide variety of technologies, such as virtual reality (Sagnier et al., 2020), social media (Choi & Chung, 2013), smart phones (Park & Chen, 2007), and machine teachers (Kim et al., 2020). Although the TAM has received some criticism (Chuttur, 2009), the present study demonstrates that the model provides a useful framework to understand the process of how people eventually decide to adopt a new technology. As such, the study suggests that the characteristics of the TAM should be considered when designing robotic health advisors.

5.2. Overall contributions and implications for robotic healthcare technology

Collectively, the present study's findings provide meaningful implications and contributions to research and practice for robotic healthcare technology. First, the present study contributes to enhancing the overall perceptions of an AI-based healthcare technology by highlighting the term, "robotic health advisor." A variety of machine agents that interact with humans are being introduced in healthcare. Some examples include chatbots that are designed to help people with depression (e.g., Fitzpatrick et al., 2017) and social robots that are designed to help improve people's psychological well-being (e.g., Scoglio et al., 2019) and physical exercise (e.g., Kidd & Breazeal, 2008). While these agents' tasks involve providing instruction or conversing about a certain health-related issue, their roles are not explicitly described as an "advisor." This distinction might be because, historically, humans have served as an advisor. Hence, the concept of a robotic health advisor, which consults with a user directly and provides suggestions to improve health, is fairly new to the public. Consequently, little information is available on how the public will perceive this type of health technology. In this regard, the present study showcases which features of a robotic health advisor could lead people to consider adopting it when this type of technology becomes available for them to use.

While people do not prefer to replace humans with machines (Rebitschek & Wagner, 2020), a robotic health advisor in healthcare may offer a variety of benefits to humans. For example, a robotic health advisor would be useful for individuals who need regular and frequent interactions to check on their health status, such as developing an exercise routine or recommending food to consume. Further, many healthcare providers do not offer counseling due to various reasons, such as time constraints during the visit and limited training on counselling (Block et al., 2003; Kolasa & Rickett, 2010). In this regard, a robotic health advisor can assist in addressing patients' needs and provide regular check-ins with less time constraints. A robotic health advisor can also be particularly helpful when people want to discuss sensitive topics. People are more willing to share sensitive or personal information with machines because they perceive machines to be objective and not judgmental

(Aroyo et al., 2018). Thus, a judgement-free robotic health advisor might be a good alternative for some people. Although patients prefer receiving care from humans, they also perceive the possible benefits that healthcare robots can bring (Vallès-Peris et al., 2021). In this regard, the present study's findings suggest a promising future in healthcare.

Although it was not tested in this present study, it seems feasible to imagine that robotic health advisors can also be used to assist with the management of mental health concerns, especially during times where individuals are socially isolated. In their article, Radanliev and De Roure (2021) discuss the importance of adopting new technologies that may help manage mental health concerns when the next pandemic occurs, which they deem "Disease X." Specifically, they highlight that a variety of technologies can be used as low-cost alternatives to those seeking therapy and healthcare during times of social isolation, such as virtual reality, music therapy, and therapeutic filmmaking. Indeed, robotic health advisors could serve in this capacity. If robotic health advisors are cost effective, accessible, and designed to provide reliable support, then they could play a valuable role in supporting health needs during a Disease X event.

Collectively, the present study's findings demonstrate that individuals deem robotic health advisors as capable of managing minor health concerns. Recall that participants viewed a video clip where a robotic health advisor gave advice regarding eating habits and weight management. Thus, the findings imply that people may find utility in robotic health advisors that are able to provide personalized health guidance and recommendations. However, it is likely that people may react differently if the robotic health advisors were making decisions about more severe health concerns (e.g., cancer, heart disease). Therefore, these findings suggest a promising supplemental role for robotic health advisors, as they can assist with improving healthcare outcomes and addressing basic needs of patients.

5.3. Limitations and future research directions

Although the present study reveals meaningful findings and provides an initial understanding to perceptions of a robotic health advisor, the study is not free from limitations. First, the study's findings are based on observational experiences rather than direct experiences of a robotic health advisor. Although this approach has been used in other studies (e.g., Merrill Jr. et al., 2022) and is useful to explore how people perceive this type of health technology, the findings would be more meaningful and applicable if an actual interaction occurred.

Second, the study measured intentions to adopt a robotic health advisor rather than actual adoption. Considering that intentions are a strong predictor for actual behaviors (Davis, 1989; Davis et al., 1989), the study's finding is meaningful in predicting actual behavior. However, there still is a need to investigate actual adoption. When robotic health advisors become more accessible and conveniently available to the public, future researchers are encouraged to address these limitations by observing direct interactions with a robotic health advisor and measuring people's visits with a robotic health advisor.

The current study also only focused on one particular health context, weight issues. Although being overweight or obese are serious health concerns (WHO, 2016), some people may consider it as a relatively minor health issue and perceive using a robotic health advisor to be acceptable for minor issues. However, for serious health concerns that require medical treatment and procedure (e.g., cancer, diabetes), people may have different views or perspectives regarding a robotic health advisor. To better understand the extent to which a robotic health advisor can be accepted, future researchers are encouraged to further investigate whether people perceive a robotic health advisor differently or similarly in various context and situations, such as types of health issues, patients' age groups, and personal factors (e.g., health history, previous healthcare technology experiences).

Further, several potentially relevant variables were not assessed when measuring perceptions of the robotic health advisor. For example, the present study did not investigate whether participants would be concerned about privacy, trust, and other related risks. Indeed, these very concerns affect how participants perceive robots designed for health, and they can ultimately affect the adoption of these technologies (Kim et al., 2023). Future research should consider how perceptions of privacy, trust, and other related risk factors influence adoption of a robotic health advisor.

Ultimately, considerable efforts should be made to find ways to establish trust with a robotic health advisor. Trust is an important factor between patients and healthcare providers, and it is a key element to positive healthcare experiences (Dang et al., 2017). Automation bias, which suggests that people hold certain expectations toward machines (Cohen et al., 1998), could influence interactions with a robotic health advisor. Thus, educating people about the capabilities of a robotic health advisor, such as its ability to provide advice and guidance, would be crucial. If trust is low, people may not accept a machine's suggestions or guidance (Gefen et al., 2003), just as one would with a human healthcare provider that they do not trust (Lo, 1999).

6. Conclusion

The present study investigated perceptions of a robotic health advisor and intentions to adopt it based on the TAM framework. Findings demonstrate that perceived ease of communication with and perceived usefulness of a robotic health advisor positively and significantly predict favorable attitudes toward a robotic health advisor, which subsequently lead to greater intentions to adopt it. Further, perceived usefulness of a robotic health advisor directly leads to an individual's intentions to adopt it. Overall, the study provides some promising suggestions for the potential adoption of robotic health advisors when they become readily available to public.

Though robotic health advisors are likely to provide a variety of benefits to those seeking care, there are still barriers that exist to implementing these advanced technologies, such as privacy concerns, cultural sensitivity, and user satisfaction (c.f., Kim et al., 2023). To ensure that robotic health advisors are used effectively and appropriately, policymakers can take several steps to ensure this possibility. First, they can develop ethical guidelines that inform the design and implementation of robotic health advisors. These guidelines can address issues related to the handling of personal health information (e.g., data security and management, consent) and ensuring inclusivity (e.g., cultural sensitivity, accessibility). Second, policymakers can also urge for transparent communication regarding the capabilities and limitations of robotic health advisors. In doing so, users will be informed about the processes that inform the output and recommendations provided by a robotic health advisor. Third, policymakers can advocate for collaboration between robotic health advisors and human healthcare providers. Robotic health advisors are meant to complement human care, not replace it. Thus, collaboration between the two can further benefit the patient and their needs. By implementing these measures, policymakers can foster responsible adoption of robotic health advisors.

Disclosure statement

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