The Social Science Journal

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/ussj20

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THE SOCIAL SCIENCE JOURNAL
https://doi.org/10.1080/03623319.2023.2289241

Trust, perceived usefulness, and intentions to adopt robotic health advisors for physical and relational health issues

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ABSTRACT

AI and robots are continuously being used in a variety of health contexts. To better understand this emerging phenomenon of employing machines in healthcare, the present research investigates trust in a robotic health advisor and intentions to adopt it by comparing a robotic health advisor designed to assist with physical health vs. relational health. An online experiment that employed a two-group comparison with a between-subjects design was conducted among 284 undergraduate students in the United States. The primary findings indicate that people report greater trust in a robotic health advisor for physical health compared to relational health, and this relationship is due to the perceived usefulness of a robotic health advisor. Additionally, trust in a robotic health advisor positively predicts intentions to adopt it. The study's findings provide meaningful implications and contributions for research and practice.

ARTICLE HISTORY
Received 26 February 2023
Revised 10 November 2023
Accepted 25 November 2023

KEYWORDS
Artificial intelligence (AI); Healthcare robots; Robotic health advisor; Trust; Human-machine communication

Over the past decade, the usage of robots in the healthcare industry has been on the rise (Cresswell et al., 2018). In particular, as artificial intelligence (AI) technology continues to advance, a variety of AI-driven healthcare robots (hereafter healthcare robots) are being employed in the medical field. For example, healthcare robots are being used in diverse fields, such as surgery (Davenport & Kalakota, 2019), psychiatry (Loh, 2018), assisting in medical diagnoses and enhancing treatments (Davenport & Kalakota, 2019), nursing (Pepito et al., 2020), and rehabilitative care (Tanioka, 2019). Accordingly, much attention has been paid to the potential of healthcare robots from an academic perspective (e.g., Kim, Merrill, et al., 2023; Kim, Song, et al., 2023).

Acknowledging the potential benefits, one additional area that healthcare robots could further contribute to is the role of a personal health advisor. Human doctors have limited availability during their office hours, which may ultimately affect the time they spend with their patients and quality of the care. In that regard, one possible way to address this issue is by adopting a robot that can serve as a personal health advisor.

To unpack this possible solution, the present study explores the role of a robotic health advisor by focusing on different types of health: physical health vs. relational health. Physical health refers to how well an individual's physical body functions (Belloc & Breslow, 1972; Huber et al., 2011). Various aspects of physical health include exercising, nutrition, sleeping behaviors, and disease prevention. Relational health refers to the overall quality of an individual's interpersonal relationships (Liang et al., 2002). Specifically, it focuses on how individuals connect and communicate with others in their social networks. Various aspects of relational health include communication, empathy, and conflict resolution skills. Relational health is

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a component of mental health, which encompasses an individual's emotional, psychological, and social well-being (Huber et al., 2011). As such, the idea of adopting a robotic health advisor implies that patients can consult with a health advisor for a variety of issues ranging from physical health (e.g., weight management, diet) to relational health (e.g., conflict, relationship issues).

Thus far, limited information is available regarding the idea of adopting a robotic health advisor. Especially, to the best of our knowledge, it is not known whether people would have different or similar perceptions of a robotic health advisor addressing physical vs. relational health issues. Thus, the present study aims to address this gap in the literature. Considering that trust is a crucial factor in healthcare (Birkhäuer et al., 2017), particularly in healthcare machines (Hengstler et al., 2016), the present study focuses on the role of perceived trust in adopting a robotic health advisor.

1. Trust and healthcare robots

1.1. Trust in AI

AI technology brings substantial and innovative changes to the society, and trust is a crucial factor in the adoption of AI. Considering that trust is a complicated and multifaceted concept (Bach et al., 2022), scholars have examined the concept of user trust in AI by using a variety of systematic and comprehensive approaches to understanding. Based on systems theory, Lukyanenko et al. (2022) developed a trust framework that provides a conceptual, theoretical, and methodological foundation for trust in AI. Additionally, Yang and Wibowo (2022) proposed a framework that explains the overall path model of trust in AI, which consists of factors influencing trust, the components of trust, and outcomes of trust.

Another line of trust research in AI is focused on causal factors for trust. Through a meta-analysis, Kaplan et al. (2023) examined psychological construct of trust in AI and its antecedents. The study finds three major categories that influence user trust in AI: human-related factors (e.g., expertise, competency), AI-related factors (e.g., performance, reliability, anthropomorphism), and contextual factors (e.g., communication, level of risks involved). Similarly, through a systematic literature review, Bach et al. (2022) investigated how user trust in AI is defined and what factors influence trust. The results suggest that user characteristics are important factors to consider, and user trust can increase over time through interactions with the AI. Also, the study highlights the importance of tailoring features of AI because different factors influence user trust differently in diverse contexts.

1.2. Trust in healthcare robots

Trust is a critical factor in healthcare, whether it is driven by a human or machine. In a traditional, human-driven healthcare context, research highlights that patient trust affects their perceptions of their healthcare providers (e.g., Birkhäuer et al., 2017; Du et al., 2020). For example, patients' trust in their physicians is positively related to patient-provider relationship building (Du et al., 2020) and satisfaction with their healthcare experiences (Van Den Assem & Dulewicz, 2014). Trust is also positively related to compliance with a healthcare provider's advice and recommendations, which naturally affects patients' healthcare experiences (Bonds et al., 2004; Meier et al., 2021). Overall, the associations between trust and positive healthcare experiences are well-supported through a systematic meta-analysis (Birkhäuer et al., 2017).

Trust is also a crucial factor in the machine-driven healthcare context, especially regarding the adoption of healthcare machines (Hengstler et al., 2016). Findings from a meta-analysis highlight that trust in healthcare technologies significantly impacts the delivery and effectiveness of healthcare (Abbas et al., 2018). Also, trust determines how people interact with a machine (Li et al., 2008). Thus, with the growing popularity of healthcare robots (Loh, 2018; Pepito et al., 2020; Tanioka, 2019), there is a strong need to examine the notion of trust in healthcare robots.

Although limited, some research has compared people's trust levels of robotic healthcare providers with human healthcare providers (e.g., Kim & Kim, 2021; Xu et al., 2018). For example, Kim and Kim

(2021) investigated how people perceive AI-based humanoid robot doctors as a primary doctor. The study found that, although the difference is minimal, trust in a robot doctor is slightly higher than a human doctor. Also, males tend to show a greater tendency to trust a robot doctor than females. On a similar vein, Xu et al. (2018) examined responses to a robot therapist compared to a human therapist and found similar levels of perceived trust in a robot therapist and a human therapist. Interestingly, the study noted that people are more likely to consider trust in their decision-making process when the therapist is a robot than a human. Overall, the findings of these studies imply the possibility that a robotic health provider may be employed in healthcare. Then, the question is in which contexts will a robotic health provider work effectively. In other words, when considering different types of health, physical vs relational, which health context would elicit greater trust in a robotic healthcare provider? One concept that could help with understanding this phenomenon is machine heuristics.

1.3. Machine heuristics and health issues for healthcare robots

Machine heuristics refer to an individual's mental shortcuts wherein they perceive a technology to be neutral, objective, and free from ideological bias when the technology demonstrates machine agency cues (Sundar, 2008). According to the Modality, Agency, Interactivity, and Navigability (MAIN) model (Sundar et al., 2015), technologies can demonstrate agency cues that indicate the source of media content, which would affect users' cognitive processing of the technologies. More specifically, when machine agency cues are presented, individuals would perceive machines to be rule-governed, accurate, objective, neutral, and infallible. Meanwhile, machines would also be interpreted as mechanistic, cold, and unemotional.

Research indicates that machine heuristics may function differently depending on the nature of the machine's tasks. Yang and Sundar (2020) systematically analyzed machine heuristics in completing mechanical tasks (e.g., mathematical operation, information storage) compared to human tasks (tasks that are mostly accepted to be unique for humans, such as creativity). Yang and Sundar noted that when machines perform mechanical tasks, attributes such as efficiency, usefulness, expertise, objectivity, accuracy, and unemotionality lead users to perceive machines to be better than humans. However, when machines perform human tasks that require creativity, intuition, and the ability to express emotions, attributes such as efficiency, usefulness, objectivity, and unemotionality lead users to perceive machines as worse than humans.

Collectively, the aforementioned argument provides a fundamental framework that people may develop different perceptions toward a robotic health advisor that performs physical health-related tasks and relational health-related tasks. Generally speaking, physical health issues (e.g., weight gain or loss) can be objectively assessed through various measures such as calorie calculations and exercise plans, which can be considered mechanical tasks. Conversely, relational health issues (e.g., conflict with a partner) may require some degree of subjective and interpretive assessment and consultation, which may be considered human tasks. Considering the nature of the machine heuristics and people's expectations about machines (Sundar, 2008) and different perceptions toward mechanical and human tasks (Yang & Sundar, 2020), the present study predicts that people would perceive greater trust in a robotic health advisor for physical health issues than for relational health issues.

H1: People will perceive greater trust in a robotic health advisor for physical health compared to relational health.

1.4. Perceived usefulness and trust

When a new technology is introduced, users' perceptions of how useful the technology can be an important factor to consider for eventual adoption (Davis, 1989). The importance of perceived usefulness is particularly crucial for machine agents, such as AI and robotic technologies. In an education context, Kim et al. (2020) examined college students' perceptions of AI-based online courses and found that perceived usefulness leads to favorable attitudes toward and intentions to take AI-based online courses. Germain to the present study's context, a research study (Kim, Merrill, Xu, et al. 2023) investigated how people perceive the potential adoption of a robotic health advisor for their physical health. The study found that perceived ease of communication with and perceived usefulness of a robotic health advisor predict positive attitudes toward a robotic health advisor, which consequently lead to stronger intentions to adopt it. Notably, the study highlights that perceived usefulness of a robotic health advisor is directly related to intentions to adopt it.

Perceived usefulness is particularly important as a mediating variable that facilitates positive perceptions of technologies. Baron and Kenny (1986) argue that a mediator explains how and why a certain effect or phenomenon occurs. Based on this argument, the present study suggests that the reason why people would perceive greater trust in a robotic health advisor for physical health compared to relational health (as predicted in H1) is because of the perceived usefulness of the robotic health advisor. That is, people would report greater perceived usefulness of a robotic health advisor for physical health (compared to relational health), which consequently would lead to greater trust in the robotic health advisor.

Although the contexts are somewhat different, this argument is in line with extant research. Kim et al. (2021) examined how people perceive different types of AI agents: functional AI vs. social/relational AI. Functional AI refers to AI that is focused on helping people complete tasks in a more efficient and effective manner, while social/relational AI refers to AI that is primarily designed to help people engage in social interactions and companionship. The study found that people show more positive attitudes toward functional AI compared to social/relational AI and it is because of the perceived usefulness of the functional AI. That is, perceived usefulness serves as a mediator in this relationship. Based on support from the literature, the current study predicts a mediating role of perceived usefulness as following.

H2: Perceived usefulness of a robotic health advisor mediates the relationship between the type of health issues (physical vs. relational) and perceived trust in a robotic health advisor.

Trust in technology is an important factor when considering the adoption of the technology (Alaiad & Zhou, 2014). Yang and Wibowo's (2022) comprehensive conceptual framework proposes that user trust in AI leads to behavioral changes, such as intentions to adopt. Empirically, the positive relationship between trust in a technology and intentions to adopt it is well-documented (e.g., Bahmanziari et al., 2003; Gefen et al., 2003; Komiak & Benbasat, 2006; Wu et al., 2008). The same pattern appears in a healthcare context. Alaiad and Zhou (2014) examined perceptions and adoptions of home healthcare robots and found that trust has a positive effect on intentions to use healthcare robots and increases the ultimate benefits one could receive from using the robot.

With current healthcare robots, the central issue may not be merely about ensuring the capability of the healthcare robot but about leading people to use it in daily clinical practice (Utermohlen, 2018). Just as patients' trust in their human healthcare providers influences patients' decisions on whether to continue to see the provider or not (Bonds et al., 2004; Meier et al., 2021), trust in a robotic health advisor could also be a critical component when considering the adoption and continued use of it. Thus, based on the above-discussed argument, the study proposes the following hypothesis.

H3: Trust in a robotic health advisor positively leads to intentions to use a robotic health advisor.

2. Methods

2.1. Overview

To test the proposed hypotheses, an online experiment was conducted by employing a two-group comparison with a between subjects design: a robotic health advisor designed to assist with physical health compared to a robotic health advisor designed to assist with relational health. Qualtrics, a survey software platform, was used to conduct the study. Participants watched video clips of a robotic health advisor and shared their perceptions and responses about it.

2.2. Materials

Video clips were edited from *The Robot Will See You Now*, a documentary released in the United Kingdom that features a newly created AI-based healthcare robot named "Jess" and its interactions with people. The primary task of Jess is to offer advice on various health-related topics and issues.

In this study, an introductory clip and two subsequent clips (one for each study condition) were edited. The introductory clip introduced Jess, the robotic health advisor, and its capabilities to give people advice and suggestions about specific issues or problems that are revealed to the robot. The introductory clip was approximately 70 seconds in length.

Then, two clips were created for each study condition where Jess interacted with a married couple, Hayley and Ronny, in a living room-like setting. For the physical health condition, the conversation focused on Hayley's weight problems. Jess asked a series of questions regarding Hayley's eating habits and weight. For the relational health condition, the conversation focused on the couple's relationship issues. Jess asked a series of questions to the couple, such as how they feel about each other and their affection for one another. The interaction reflected a real-life situation and Jess conversed with both Hayley and Ronny. Both clips were approximately two minutes long.

2.3. Procedure

Participants were recruited from undergraduate courses at a large, urban, and public university in the United States. Upon receiving approval from the university's Institutional Review Board (IRB), a recruitment message was sent to potential participants. Interested individuals were instructed to click on a link that was included in the recruitment message. After acknowledging the informed consent, participants were instructed that they would watch two short video clips and share their perceptions about what they saw in the clips. A timer was set for each clip, so that the participants did not proceed without watching the clips in full. Participation was voluntary, and all participants received extra credit. Confidentiality was guaranteed.

2.4. Data cleaning and sample

Initially, 323 individuals completed the study. To ensure the quality of the data, a series of data screening processes were performed. First, 18 individuals reported that they had completed the study more than once; thus, their responses after the first attempt were removed. Second, two individuals failed an attention check while completing the study; thus, their responses were removed. Third, to ensure that participants watched the stimulus clip, a question asked about the primary health issue that the robotic health advisor discussed in each condition. Ten individuals (six in the physical health condition, four in the relational health condition) failed to correctly identify the health issue; thus, their responses were eliminated. Finally, nine individuals reported that they had watched the clip before; thus, their responses were deleted to avoid any potential bias from their previous exposure to the stimuli.

After the data cleaning process, a total of 284 individuals remained in the final sample. The sample consisted of 185 females (65.1%) and 99 males (34.9%), and the average age of the participants was 21.94 years ($SD = 4.18$). Majority of the participants were White/Caucasian ($n = 157$: 55.3%), followed by Latine or Hispanic ($n = 61$: 21.5%), Black/African American ($n = 35$: 12.3%), Asian ($n = 22$: 7.7%), and other ethnic groups ($n = 9$: 3.2%). Further, 140 participants (49.3%) were randomly assigned to the relational health condition, and 144 participants (50.7%) were randomly assigned to the physical health condition.

2.5. Measures

A series of questions were asked to assess perceptions about a robotic health advisor, Jess. *Perceived usefulness* ($\alpha = .95$) was measured with four items (e.g., "A robot similar to Jess would enhance the quality of my life" and "... would be useful for many things in my life"). Responses were obtained on a 7-point Likert scale (e.g., 1 = *Strongly Disagree*, 7 = *Strongly Agree*). Items were adopted from Davis (1989).

Trust ($\alpha = .90$) was measured with 12 items. Example items included "I think Jess, the robot, was ... '*Unreliable—Reliable*' and '*Undependable—Dependable*.'" Responses were obtained on a 7-point semantic differential scale. Items were adopted from Elkins and Derrick (2013).

Intentions to adopt ($\alpha = .94$) were assessed with three items (e.g., "If a robot similar to Jess is available, I might try it" and "... I would be interested in adopting it"). Responses were obtained on a 7-point Likert scale (e.g., 1 = *Strongly Disagree*, 7 = *Strongly Agree*). Items were adopted from Choi and Ji (2015). A complete set of measures and study materials are available upon request from the corresponding author or here: https://osf.io/qse75/?view_only=a4cc545be1ab456f96714864a0247db9.

3. Results

Before the primary analyses, zero order correlations between all study variables were assessed (see Table 1). To examine H1 (main effect of the health issue) and H2 (mediation effect), PROCESS model #4 (Hayes, 2017) was used based on 5,000 bootstrap samples. PROCESS was chosen over Structural Equation Modeling (SEM) because when testing simple mediation models, PROCESS is more efficient than running SEM and there would not be any differences in results between the two programs (Hayes, 2017). The results were assessed based on a 95% Confidence Interval (CI). The health issue (relational = 0; physical = 1) was dummy coded. For all tests, demographic information (sex and age) was included as covariates.

H1 predicted that people would show greater trust in a robotic health advisor for physical health issues compared to relational health issues. Results from the PROCESS model found that there was a statistically significant main effect of the health issue (total effect = .53; $SE = 0.12$; CI = [0.29, 0.76], $p < .001$). Results from an ANCOVA confirmed that participants perceived greater trust in the robotic health advisor for physical health issues ($M = 5.13$, $SD = 0.85$) compared to relational health issues ($M = 4.61$, $SD = 1.12$), $F(1, 279) = 19.71$, $p < .001$, $\eta_p^2 = .0664$. H1 was supported.

H2 predicted that perceived usefulness of a robotic health advisor mediates the relationship between the health issues (relational vs. physical) and trust in a robotic health advisor. The results revealed a significant mediation effect of perceived usefulness ($B = .30$, $SE = .07$, CI = [0.17, 0.42]). Participants in the physical health condition, compared to the relational health condition, reported greater perceived usefulness of a robotic health advisor (a = 0.80), which led to greater trust (b = 0.38). H2 was supported. Neither sex nor age was significant in the analyses for H1 and H2. See Figure 1 and Table 2.

H3 predicted that trust in a robotic health advisor positively leads to greater intentions to use a robotic health advisor when it becomes available. To test H3, a regression analysis was conducted. Considering that the health issues and perceived usefulness were included in H1 and H2, which were concerned with trust, both variables and two demographic variables (sex and age)

Table 1. Zero-order correlations, means, and standard deviations for tested variables.

	1	2	3
1. Usefulness	1		
2. Intention to adopt	−.49**	1	
3. Trust	.17**	−.07	1
M	4.68	1.84	4.67
SD	1.05	0.58	1.20

**$p < .01$(2-tailed).

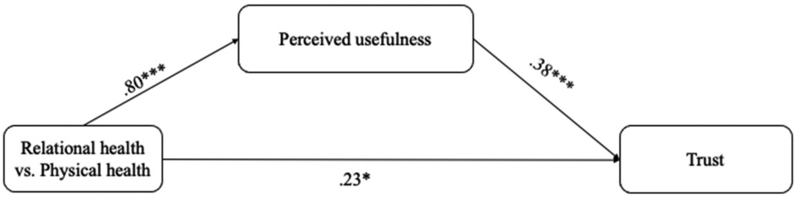

Figure 1. Final mediation model (H1 & H2). Direct effect: .23 [.02, .43]; Indirect effect: .30 [.17, .45]; Total effect: .53 [.29, .76] *$p < .05$, **$p < .01$, ***$p < .001$.

Table 2. Results of mediation analyses (H2).

		95% Confidence interval	
Effect health vs. relational health	*B (SE)*	*LLCI*	*ULCI*
Total effects	.53 (.12)	.29	.76
Direct effects	.23 (.10)	.02	.43
Indirect effects	.30 (.07)	.17	.45

B: unstandardized effect. *SE*: standard error. *LLCI*: lower-level confidence interval. *ULCI*: upper-level confidence interval.

were entered in Model 1 as control variables and trust was entered in Model 2 to assess the unique contribution of trust on intentions. Overall, Model 2 accounted for significant variance of users' intentions to use a robotic health advisor [$\Delta R^2 = .02$, $F(5, 277) = 102.28$, $p < .001$]. While controlling for the health issue, perceived usefulness, sex, and age, trust in a robotic health advisor positively predicted intentions to use it ($\beta = .17$, $t = 3.90$, $p < .001$). H3 was supported. See Table 3 for the complete results of H3.

4. Discussion

The present research explores whether people show different levels of trust in a robotic health advisor designed to assist with physical or relational health. Findings indicate that people perceive greater trust in a robotic health advisor designed to assist with physical health compared to relational health, and this relationship is due to the perceived usefulness of the robotic health advisor designed to assist with physical health. Additionally, trust in a robotic health advisor positively predicts intentions to adopt it when it becomes available. The following section discusses these findings along with implications and contributions. Then, the study ends with limitations and future research directions.

4.1. Primary findings and implications

The present study finds that people perceive greater trust in a robotic health advisor for physical health compared to relational health. This finding may be partially explained by the nature of machine heuristics, which explain that machines are perceived to be objective and accurate (Sundar, 2008). Thus, people may place stronger trust in a robotic health advisor that deals with weight issues (physical health), which can be managed with accurate measurements of diet and exercise to achieve a goal, compared to relationship issues (relational health), which typically involve emotions and feelings that may not be fully assessed with numbers or statistics.

This finding implies that a robotic health advisor could be a beneficial tool to help people manage their physical health on a regular basis. In the current market, there exist a good deal of health-related applications, such as fitness trackers. This type of health-related application can be effective (Stiglbauer et al., 2019). However, an interaction with an application might be less engaging compared to an interaction with a robotic health advisor, which is designed to be similar to a human healthcare

Table 3. Multiple regression: trust predicting intentions (H3).

			Outcome Variable
Predictor Variables			Intention
Model 1		R^2	.63
		F	118.00***
	Sex	β	−.09
	Age	β	.00
	Health issue	β	−.06
	Usefulness	β	.79***
Model 2		ΔR^2	.02
		ΔF	15.24***
	Sex	β	−.10**
	Age	β	.00
	Health issue	β	−.08*
	Usefulness	β	.69***
	Trust	β	.17***

Health issues (dummy coded: 0 = relational health, 1 = physical health), Sex (dummy coded: 0 = male, 1 = female)
*$p < .05$, **$p < .01$, ***$p < .001$.

provider. Thus, this finding suggests that using a robotic health advisor could be an effective strategy for helping people with physical health management.

The present study also finds a significant mediating role of the perceived usefulness of a robotic health advisor. Participants perceived that a robotic health advisor for physical health is more useful than for relational health, and the perceived usefulness leads to greater trust in a robotic health advisor. Although the contexts are somewhat different, this finding is in line with extant research, which found that people perceive task-oriented AI to be more useful than social/relational AI, and perceived usefulness leads to positive perceptions of the AI (Kim et al., 2021).

Acknowledging the importance of trust in positive health outcomes and experiences (e.g., Birkhäuer et al., 2017; Du et al., 2020), this finding highlights the need to identify ways to foster perceived usefulness. Research indicates that social influence has a significant impact on the perceived usefulness of a technology (Venkatesh & Davis, 2000). If someone believes that others have positive evaluations of a technology, then they may consider adopting the technology (Venkatesh & Davis, 2000). Thus, when a robotic health advisor becomes more readily available, sharing positive reviews of other users might be an effective way to promote the perceived usefulness of a robotic health advisor.

Further, the study reveals that trust in a robotic health advisor leads to intentions to adopt it when it becomes available. In fact, this finding is consistent with the conceptual framework of user trust in AI (Yang & Wibowo, 2022) as well as empirical research that documents a positive relationship between trust in a technology and intentions to adopt it (e.g., Bahmanziari et al., 2003; Gefen et al., 2003; Komiak & Benbasat, 2006; Wu et al., 2008). In a healthcare context, if people do not trust their healthcare provider, they might change their provider (Bonds et al., 2004; Meier et al., 2021). The present study's finding suggests that the same tendency may appear for robotic healthcare providers.

This particular finding provides useful implications for practice. Trust in technology, or the belief that robots are reliable, effective, and honest in providing healthcare services, would help reduce doubt and hesitancy in adopting technologies. Thus, the finding implies that the robotic healthcare industry should focus on building trust among potential adopters. One possible way to foster trust might be incorporating effective communication styles of a robotic health advisor. Pelau et al. (2021) revealed that robots' ability to express empathy when communicating with humans is an essential component in promoting trust in robots. By incorporating effective communication styles through verbal and nonverbal cues, robot developers could find ways to successfully build trusted robotic health advisors or healthcare robots, broadly.

4.2. Overall implications and contributions

As a whole, the present study provides several meaningful implications and contributions. First, the study suggests that people could develop trust in healthcare robots for both physical and relational health, revealing that the level of trust in a robotic health advisor is higher than the mid-point in each condition. Specifically, in the physical health condition, a one sample t-test revealed that trust in a robotic health advisor ($M = 5.13$, $SD = 0.85$) is greater than the mid-point of the trust level (3.5 on a scale of 7), $t(1, 143) = 23.06$, $p < .001$. The same result is also found in the relational health condition, such that trust in a robotic health advisor ($M = 4.61$, $SD = 1.12$) is greater than the mid-point of the trust level (3.5 on a scale of 7), $t(1, 139) = 11.65$, $p < .001$.

Related to the abovementioned, the perception of trust in a robotic health advisor implies that the general public might be prepared to accept the integration of healthcare robots. This notion indicates that during circumstances like the COVID-19 pandemic, where human vulnerabilities to an infectious virus became apparent, the implementation of healthcare robots could be an effective approach to safe healthcare (Kaiser et al., 2021; Singh et al., 2021).

Further, a robotic health advisor may be implemented in healthcare for relational and physical health in unique ways. Medical science draws upon research, established guidelines, and evidence-based practices to address physical health problems (Citrome & Yeomans, 2005; Gronholm et al., 2021). Thus, robotic health advisors can use this information to make subsequent recommendations to patients. Relational health, on the other hand, involves communication and interpersonal dynamics, which can be more complex and subjective (Liang et al., 2002). These dynamics make relational health problems difficult to solve, as one must account for the uniqueness of each relationship and the individuals involved. However, advancements in technologies have made it possible for AI to address relational health problems. Specifically, AI may be able to analyze communication patterns, identify areas of conflict, and suggest strategies for improved communication and relationship building.

Next, the study's findings suggest that a robotic health advisor can assist human healthcare providers. Generally, people do not want machines to replace humans (Rebitschek & Wagner, 2020), and this tendency may be stronger when discussing one's health. However, considering humans' expectations that machines could perform better than humans in some areas (Cohen et al., 1998; Lee & See, 2004), some may benefit from communicating with a robotic health advisor. Especially, given that human healthcare providers have time constraints in providing medical services (Block et al., 2003; Kolasa & Rickett, 2010), adopting a robotic health advisor as an assistant, particularly for physical health issues, would be an effective strategy for addressing patients' needs. Adoption of these technologies can potentially help human healthcare providers focus on addressing patients' relational or social health issues or other areas that machines may not perform effectively.

The study also contributes to expanding the extant literature by addressing how human perceptions, especially trust, can change across different contexts. The current body of literature has documented various factors that affect how individuals perceive robots. For example, empirical research has documented that a robot's tone of voice (e.g., Moridis & Economides, 2012), pitch (e.g., Edwards et al., 2019), and gestures (e.g., Kose-Bagci et al., 2009) all influence perceptions and experiences of robot interactions. Though previous research has found that a variety of factors impact trust in robots (e.g., Bach et al., 2022; Kaplan et al., 2023), limited research focuses on how content or the subject of the conversation with AI or robots would affect trust. In this regard, the present study contributes to creating new knowledge in the extant literature.

In all, though robotic health advisors are likely to provide a variety of benefits to users, it is important to note that they can also generate unanticipated answers that may be incorrect or flawed. AI is trained on large amounts of data, but it can still make errors due to limitations in the data or algorithmic biases (Nelson, 2019). It is also possible that the AI might encounter a situation in which it was not specifically trained for, which may lead to unexpected responses. These responses could potentially have a negative effect on one's health.

To address these concerns, users may be required to read and agree to a terms of use or a disclaimer before engaging with a robotic health advisor. These legal documents will inform users about the capabilities and limitations of robotic health advisors and will explicitly state that the recommendations provided by them may be subject to error. Further, users should be informed that they must exercise caution when using robotic health advisors and consider seeking additional medical advice when necessary. Another way to address these concerns is to require developers to continuously evaluate and improve the AI systems that are used for robotic health advisors. In doing so, developers can minimize risks of using robotic health advisors and patients can perceive them as trustworthy and reliable. Regardless, legislation must account for these possibilities to ensure that patients and their data are protected.

4.3. Limitations and future research directions

Although the present study reveals interesting findings, the study also acknowledges a few limitations that should be addressed in future research. First, the present study used a convenience sampling method and only recruited college students. Though data screening processes were performed thoroughly to ensure the quality of the data, a sample of college-aged students may not fully represent the characteristics of the general population. Also, considering that the notion of a robotic health advisor is a fairly advanced technology, which college students might be more open to try, it might be possible that somewhat different patterns may appear in other age groups. In order to capture a better understanding of this phenomenon, the study calls for similar investigations with other age groups and/or nationally representative groups.

Second, the study employed an indirect exposure with a robotic health advisor via video clips rather than a direct interaction with a robotic health advisor. Because a robotic health advisor is not commonly used yet, the use of video clips is helpful in understanding how people would perceive and react to these types of healthcare robots when they become available for the public to use readily. In fact, this approach of using video clips is commonly used when conducting research on new technologies (c.f., Kim et al., 2021; Merrill et al., 2022). However, when robotic health advisors become more incorporated into the current healthcare system and readily available, future research should investigate responses to robotic health advisors via direct interactions.

Next, because the present study is cross-sectional, it is not clear whether the findings will change or remain over time. Considering that individuals generally interact with their health advisors or healthcare providers over time, there is a need to understand how perceptions and responses toward a robotic health advisor may change over time through multiple interactions. In fact, trust can increase over time as users continue to interact with AI or AI-based agents (Bach et al., 2022). Thus, the study calls for longitudinal research.

Lastly, the current study only examined one aspect of a robotic health advisor, which focused on the type of health issues it was designed to address. Thus, future researchers are encouraged to address a variety of other potentially relevant variables. For example, it would be meaningful to compare a robotic health advisor and a human health advisor to understand how people respond differently or similarly. Also, it would be interesting to examine how critically people evaluate bad advice of a health advisor when it is robot compared to a human.

5. Conclusion

AI-driven healthcare robots have the potential to transform healthcare services for patients, healthcare providers, healthcare administrators, and the health industry, as they can contribute to the "quantity, quality, and safety of the patient care" (Ruiz-Del-Solar et al., 2021, p. 83). In an attempt to better understand this new phenomenon, the present research examined trust in a robotic health advisor and intentions to adopt it. The primary findings indicate that people develop greater trust in a robotic health advisor designed to assist with physical health issues compared to relational health issues, which is explained by greater perceived usefulness of a robotic health advisor. Additionally, trust in a robotic health advisor positively predicts intentions to adopt it. Trust in AI technology has significant real-world impacts in human-AI or human-machine interactions (Kaplan et al., 2023), and trust in healthcare has crucial impacts on patient healthcare (Du et al., 2020). In this regard, the present study stresses a strong need for more research to better understand how to build trust in patient-healthcare robot interactions.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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