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RESEARCH ARTICLE

Exploring the effect of perceived empathy and social presence on the intention to use AI in higher education

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Abstract

Existing studies that examine the determinants of acceptance and use of health chatbots have often reported inconsistent results. These studies have also predominantly focused on utilitarian factors (such as usefulness and ease of use) to explain health chatbot use behavior. This study examined how human-social characteristics of health chatbots influence user perceptions and continuous use intentions. A research model was deductively developed using inferences from prior studies. A survey questionnaire was employed to gather responses from 348 respondents. The results from the partial least square structure equation modeling analysis revealed that perceived enjoyment, perceived usefulness, and perceived ease of use are significant predictors of continuous use intentions. Also, perceived social presence, perceived attractiveness, and perceived ease of use, significantly influence perceived enjoyment and perceived liking. The findings emphasize that both human-social characteristics influence users to appreciate the functionality and utility of health chatbots which consequently motivates continuous use intentions.

Keywords: Perceived empathy, Artificial intelligence, Adoption, Higher education, Chatbots.

Introduction

Artificial intelligence (AI) technologies, particularly chatbots, have penetrated many aspects of human lives. Chatbots are AI programs designed to simulate human-like conversations with users *via* text-based or voice-based interfaces (Palanica *et al*., 2019). In the last decade, chatbots have been used in different sectors of our society, including education, e-commerce, banking, and health. In health, chatbots have been used for diagnosing diseases (Fan *et al*., 2021), facilitating training of health professionals (Baglivo *et al*., 2023), as well as offering behavior and mental health support (Pereira *et al*., 2019). Studies have shown that health chatbots provide convenient and immediate access to health information (Xiao *et al*., 2023), personalized health-related services (Miura *et al*., 2022), and augment patient anonymity (Pereira *et al*., 2019). Chatbots, thus, can be harnessed to address several healthcare-related challenges, such as access, affordability, and quality of care, particularly in developing societies (Sallam, 2023).

Despite the popularity and potential of chatbots in the health sector, academic research in the domain is still infant (Liu *et al*., 2024). Previous studies that have investigated the use, acceptance, and/or adoption of health chatbots have reported inconsistent results and do not fully explain what factors influence health chatbot use. This current study attributes this to the predominately focus on utilitarian factors and are commonly framed by traditional technology acceptance theories such as the technology acceptance model (TAM) (Davis, 1989) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh *et al*., 2003). For instance, using the UTAUT as a theoretical lens, van Bussel *et al.* (2022) found that perceived usefulness and ease of use are key determinants for users' intention to adopt health chatbots. Similarly, Kim *et al.* (2021) found that perceived usefulness can influence users' acceptance of health chatbots for managing tuberculosis disease. This current study opines that prior studies' predominant focus on utilitarian/technological factors does not fully explain user perceptions and intentions about health chatbots.

Recent studies in other domains have demonstrated that human-social characteristics of a computerized system (e.g., chatbot) can affect users' interactions and perceptions

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of the system. For example, findings from Heerink (2011) showed that perceived social presence can influence adult users' acceptance of assistive robots. Extant studies have also shown that the perceived attractiveness of a technology (which is a human-social characteristic) can influence users' perceptions of the technology (Bahmanziari *et al*., 2003). It is possible that the human-social characteristics or cues incorporated in health chatbots can elicit positive responses that could influence users' perceptions of the chatbot (Toader *et al*., 2019). Yet, existing studies do not fully account for the relevance of these social dimensions of health chatbots in explaining their usage.

This study, therefore, attempts to extend existing research by investigating how health chatbot human-social characteristics influence African users' intentions toward health chatbots. Specifically, this current study examines how TAM constructs (i.e., perceived usefulness and perceived ease) and perceived human-social characteristics of health chatbots (i.e., perceived social presence, perceived attractiveness, perceived enjoyment, and perceived liking) together influence users' continuous use intentions. Thus, the study advances our knowledge of how these human-social characteristics influence users' interactions with health chatbots and offers a more comprehensive view of user behavior. For designers and developers, the findings offer actionable insights on how to create health chatbots that are not only efficient but also engaging and appealing. Finally, this study addresses the limitations of existing studies by focusing on the African region. Given the unique challenges faced by developing societies, such as issues related to access, affordability, and quality of care, this research provides valuable insights for designing context-specific health interventions for the region. The next section provides a review of existing literature. This is followed by hypotheses formulation before the detailed methodology of the study is presented. Next, the results from the data analysis and the findings are discussed. Finally, implications for future research are outlined.

Literature Review

Accessible and quality healthcare services have become a widespread phenomenon across many countries and continents. Accessible healthcare enables individuals to receive timely and appropriate treatments, which can lead to better health outcomes such as reduced mortality rates (Baker *et al*., 2020), improved life expectancy (Zarulli *et al*., 2021), and enhanced quality of life. Patterson (2023) argued that accessible and quality health care enhances the overall capabilities of a country's workforce and can drive productivity and economic growth. Certainly, this fundamental importance of the healthcare sector motivates the United Nations Sustainable Development Goal 3, which seeks to To ensure healthy lives and promote well-being for all at all ages by 2030 (United Nations, 2024). However, the healthcare sector faces major challenges due to inadequate health personnel and facilities to complement the rapid increase in the world's population growth. Recent studies suggest that these challenges may heighten in the next few years. For example, based on statistics from the Association of American Medical Colleges (AAMC), Lagu *et al*., (2022) predict a further shortage of around 120,000 physicians by 2032. In Africa, studies have already shown a shortage of healthcare workers (Cerf, 2021; Ahmat *et al*., 2022).

The ability of health chatbots to communicate in different languages also fosters patient-centered care and improves accessibility to healthcare information (Brandtzaeg & Følstad, 2017). Lucas *et al*. (2014) revealed that health chatbots can quickly connect with patients and effectively offer mental health services, such as coping strategies and relaxation techniques. This is because health chatbots are non-judgmental and impartial, thus, patients are more comfortable and are more willing to disclose their symptoms (Lucas *et al*., 2014; Lucas *et al*., 2017). Due to these benefits enabled by health chatbots, some studies (e.g., Wutz *et al*., 2023) have asserted that they may be more effective in providing healthcare services for some patients in some areas. For example, in many African societies where women may be stigmatized for seeking sexual reproductive health education (Morris & Rushwan, 2015), health chatbots could be adopted to provide anonymous and non-judgmental health services.

However, findings from other studies provide contradictory evidence on the significance of some of the aforementioned factors that influence users' intentions toward health chatbots. Particularly, a critical review of the relevant literature implies that the significance of the determinants of health chatbot adoption and/or use is inconsistent. For instance, in contrast to findings from prior studies (e.g., Almalki, 2021; Issom *et al*., 2021; Dhinagaran *et al*., 2021), Huang *et al*. (2021) found no significant relationship between users' perceptions of ease of use and their intentions to adopt Health Chatbot for weight management. Whereas, Dhinagaran *et al*. (2021) observed a significant effect of hedonic motivation on the intention to use health chatbots, Laumer *et al*. (2019) found no significant relationships between the two constructs. That is, many existing studies have reported variations with regard to factors that affect the adoption and use of health chatbots (Nadarzynski *et al*., 2019). There is, therefore the need for more investigations into other salient factors that can affect health chatbot use.

Yet, existing studies provide limited evidence on how human-social characteristics affect health chatbot adoption and use. Existing studies have rather focused on utilitarian system characteristics (e.g., usefulness), which are often founded on traditional acceptance theories such as the technology acceptance model (Davis, 1989) and the unified theory of acceptance and use of technology (Venkatesh *et al*., 2003). However, these theories do not adequately capture or explain how human-social characteristics of technological systems affect their adoption, acceptance, and/or use. Meanwhile, and as shown in this review, human-social characteristics that are incorporated in chatbot design can influence use behavior. This study will thus attempt to uncover how certain human-social characteristics (e.g., social presence and attractiveness) affect users' perceptions of health chatbots.

Theoretical Foundation

This current study adopted the technology acceptance model (TAM) (Davis, 1989) to address the research objective espoused above. TAM is a theoretical model that explains and predicts user acceptance of technology. It has been widely used in the field of information systems to understand how users come to accept and use technology. Numerous empirical studies across various contexts and technologies have validated TAM, demonstrating its reliability and validity in predicting technology acceptance and usage (Marangunić & Granić, 2015). The model suggests that two primary factors (i.e., perceived usefulness and perceived ease of use) influence an individual's decision to use a technology. As indicated earlier, TAM has a limited focus and may not capture certain factors (e.g., social factors) that are influential in technology acceptance (Masrom & Hussein, 2008). However, TAM can be extended and adapted to different contexts by incorporating additional variables (Masrom & Hussein, 2008). Following this approach, this current study incorporates four (4) new constructs with the TAM's primary factors to explain how they affect user intentions. Specifically, perceived social presence, perceived attractiveness, perceived enjoyment, and perceived liking are integrated with perceived usefulness and perceived ease of use to explain users' continuous use intentions.

Hypotheses Formulation

Figure 1 is a graphical illustration of the proposed relationship among the constructs. Figure 1 proposes that perceived social presence is a significant determinant of perceived enjoyment and perceived liking.

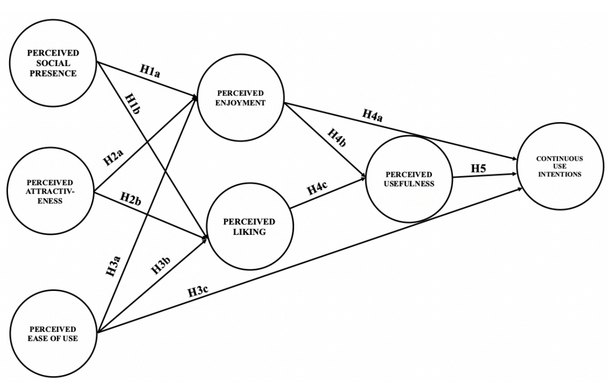


Figure 1: Research model

Perceived social presence is defined as the degree to which a health chatbot is perceived as a social entity capable of engaging in human-like interactions (Tsai *et al*., 2021). It refers to the extent to which health chatbot users feel that they are interacting with a social entity rather than a machine (Hew *et al*., 2023). This includes the chatbot's ability to mimic human-like interactions, emotional expressiveness, and the use of social cues. The social presence theory (Short *et al*., 1976) posits that the presence of social cues and human-like interactions in communication elicit emotional responses from people. When users feel that the chatbot is genuinely interacting with them, they are more likely to find the experience enjoyable. Bickmore and Picard (2005) demonstrated that relational agents capable of building social-emotional relationships with users significantly enhance user enjoyment and engagement. Likewise, evidence from studies in other domains has found that a chatbot's social presence enhances user engagement and enjoyment. Abror *et al.* (2020) also suggested that a chatbot's social presence can affect its likability. Therefore, this study argues that:

H1a: Perceived social presence has a significant effect on perceived enjoyment.

H1b: Perceived social presence has a significant effect on perceived liking.

The research model also predicts that perceived attractiveness has a significant influence on perceived enjoyment and perceived liking. Perceived attractiveness refers to the degree to which a user finds a health chatbot visually appealing based on its design or appearance (Go & Sundar, 2019). According to the aesthetic usability effect (Hassenzahl, 2004), people often perceive aesthetically pleasing designs as more usable and enjoyable, even if their functionality is not superior. If a health chatbot is perceived as attractive, users are likely to view it more positively. In other words, attractive health chatbots can create a positive impression that influences the overall user experience. Studies (e.g., Bubaš *et al*., 2023; Deci & Ryan, 2013) have shown that the positive affect derived from attractiveness can enhance enjoyment and liking. Hence;

H2a: Perceived attractiveness has a significant effect on perceived enjoyment.

H2b: Perceived attractiveness has a significant effect on perceived liking.

Perceived ease of use is also proposed as a determinant of perceived enjoyment and perceived liking. Perceived ease of use refers to the extent to which a user believes that interacting with a health chatbot will be free of effort (Davis, 1989). According to Deci and Ryan (2013), ease of use can impact intrinsic motivation. When a system is easy to use, it reduces the cognitive effort required by the user. This reduction in effort can positively influence users' attitudes and their overall satisfaction with the system (Esteban-Millat *et al*., 2018). Similarly, when a health chatbot is easy to use, users experience less frustration and more satisfaction, which can enhance their enjoyment and liking of the system. This is corroborated by findings from Kasilingam (2020) and De Cicco *et al*. (2021). Consequently, the study hypothesizes that:

H3a: Perceived ease of use has a significant effect on perceived enjoyment.

H3b: Perceived ease of use has a significant effect on perceived liking.

H3c: Perceived ease of use has a significant effect on continuous use intentions.

The study also hypothesized that perceived enjoyment and perceived liking both have significant effects on perceived usefulness and continuous use intentions. Perceived enjoyment refers to the extent to which a user finds interaction with a health chatbot pleasurable and satisfying (Ashfaq *et al*., 2020). Perceived liking is the degree to which a user feels positively about a health chatbot (De Cicco *et al*., 2021). The self determination theory (Short *et al*., 1976) suggests that enjoyment and positive feelings about an entity are important for continued engagement. When users like and find interaction with a system enjoyable, their intrinsic motivation increases (De Cicco *et al*., 2021). This heightened motivation can enhance their perception of the system's usefulness. Moreover, enjoyable experiences often lead to positive reinforcement (Müller *et al*., 2019). Users who enjoy their interactions are not only more likely to perceive the system as useful but may be motivated to continue using it. Therefore, the study suggests that:

H4a: Perceived enjoyment has a significant effect on continuous use intentions.

H4b: Perceived enjoyment has a significant effect on perceived usefulness.

H4c: Perceived liking has a significant effect on perceived usefulness.

Lastly, the study proposed that perceived usefulness has a significant effect on continuous use intentions. Perceived usefulness denotes the degree to which users believe that using a health chatbot enhances their performance or health tasks (Davis, 1989). TAM (Davis, 1989) posits that perceived usefulness has a direct impact on users' attitudes and their behavioral intentions toward the technology. Specifically, users continued use intentions are largely driven by whether the system meets their expectations for usefulness (Fan *et al*., 2021). Extant studies have also provided evidence of a significant relationship between perceived usefulness and continuous use of technology in diverse sectors, including online health information systems (Ashfaq *et al*., 2020) and mobile learning (Ghazali *et al*., 2020). This current study, therefore, expects that:

H5: Perceived usefulness has a significant effect on continuous use intentions.

Materials and Methods

As indicated earlier, this current research aims to evaluate specified hypotheses that were generated from previous studies. As a result, the deductive research approach is adopted to validate the research model.

Participants

The current study employed convenience sampling to invite one thousand students from the University of Professional Studies, Accra, Ghana to partake in the study. Participation was voluntary. After a month of data collection, 351 responses were retrieved, which represents a response rate of 35%. After reviewing the gathered responses (n = 351), responses from 3 participants were removed because they were not users of any health chatbot. That is, 348 valid responses were used for the analysis. The descriptive analysis revealed the mean age of respondents as 25 years, with a standard deviation of 4.1. The majority (73%) of respondents were male, 23% were female, and 4% declined to reveal their gender. Additionally, 69% considered themselves to have intermediate computing skills, whereas 31% reported having advanced computing skills. As indicated, all respondents had used chatbots such as Ada Health Your MD, Buoy Health, and ChatGPT for health and wellness purposes. Approximately 30% of the respondents were daily users of health chatbots, 25% were weekly users, and the remainder (45%) were monthly users.

Materials

An online questionnaire designed using Google Forms was employed to gather participants' responses. The questionnaire was designed in English and had four different sections. The first section of the questionnaire presented a short description of the aim of the study. The first section also assured participants that the study was an academic exercise, and their responses were anonymous. In the second section, participants' demographic information, including age, gender, educational background, and perceived computing skills, was recorded. The next section (i.e., section 3) gathered participants' perceptions of the key constructs of the study: (i) Perceived social presence, (ii) perceived attractiveness, (iii) Perceived ease of use (iv) Perceived enjoyment (v) Perceived liking, (vi) Perceived usefulness (vii) Continuous use intentions. All the questions used to measure the constructs were adapted from prior studies (Davis, 1989; Ghazali *et al*., 2020) to fit the context of the study. Also, each construct was measured with at least three (3) items, designed on a five-point Likert scale ranging from «Strongly Agree (5)» to Strongly Disagree (1)». In the final section of the questionnaire, participants were debriefed and thanked.

Procedure

An initial pretest was conducted with thirty participants from a different university in Ghana. This was to ensure that questions were reliable and easily understood. The analysis of the pretest responses confirmed that all questions were reliable and clear. Next, an invitation that contained a link to the online questionnaire was shared with potential participants via email. After agreeing to the informed consent requirements, participants were asked if they were users of any health chatbot. Participants were also required to report the health chatbots they use. Next, participants were presented with the four-section questionnaire. The questionnaire described the aim of the study and gathered information about their demographics, as well as their perceptions of the observed constructs of the study. The last section of the questionnaire presented the debriefing information and appreciation message. No remuneration was given for participation.

Data Analysis

The partial least square structural equation modeling (PLS-SEM) technique was employed to evaluate the proposed relationships. PLS-SEM also provides rigorous techniques for handling errors from multivariate distributions (Hair *et al.*, 2019). More importantly, PLS-SEM is a potent technique that allows researchers to estimate predictive relationships between constructs (Hair *et al.*, 2014). It is thus appropriate for testing the significance of independent variables on the dependent variable (Hair *et al.*, 2019). PLS-SEM is, therefore, adequate for evaluating research models that attempt to extend existing theories and frameworks. Hence, SmartPLS 4.0 software was adopted to evaluate the measurement and structural models.

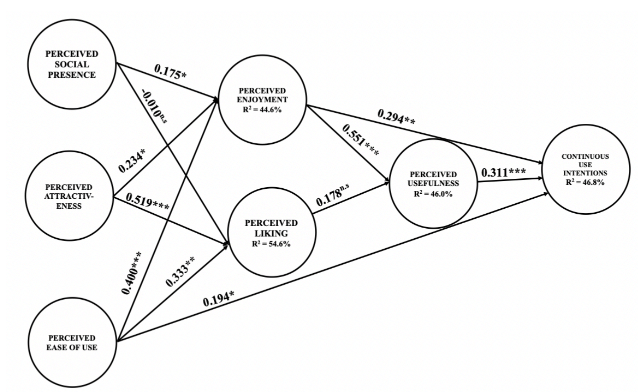
Measurement Model

The measurement model analysis evaluates the reliability and validity of the research model (Hair *et al.*, 2011). In this study, all question items used for measuring the constructs were designed to be reflective. This is because the question items were highly reflective and interchangeable. In line with Hair *et al.* (2019) measurement model was analyzed based on item reliability, internal consistency, convergent validity, discriminant validity, and multicollinearity. Questions items that had loadings greater than 0.70 were deemed as reliable. For internal consistency, the Cronbach alpha and composite reliability values were juxtaposed to the required minimum threshold of 0.70 (Hair *et al.*, 2019). The average variance extracted (AVE) was adopted to measure convergent validity. From the AVE values from Table 1, it is evident that a convergent validity minimum requirement of 0.5 was achieved (Hair *et al.*, 2019; Hair *et al.*, 2011). For brevity, only the results of internal consistency and convergent validity are shown in Table 1.

Discriminant validity was measured with the Heterotrait-Monotrait ratio (HTMT). Clark and Watson (2016), assert that HTMT values lesser than 0.85 determine discriminant validity. Table 2 shows all HTMT values were lesser than the suggested requirements. Lastly, the possibility of collinearity was assessed using the variable inflation factor (VIF) of the constructs. Table 2 shows the VIF values (in brackets) of all constructs and indicates that the values were within the maximum threshold of 3 as required by Hair *et al.* (2019).

Structural Model

The structural model evaluates the significance of the proposed relationships. The Bootstrap technique (5000 samples) was used to test the significance of the hypothesized relationships. Following Hair *et al.,* (2013) the explanatory power of the model was explained using accumulated Variance (R^2) of the exogenous variables. R^2 values were also interpreted as irrelevant (R^2<0.25), small (R^2> = 0.25), medium (R^2> = 0.50), and large(R^2> = 0.75).



(Note: p***<0.001, p**<0.005, p*<0.05, $p^{n.s}$ – not significant).

Figure 2: Structural model

Table 1: Construct validity and reliability

	Cronbach's alpha	*Composite reliability (rho_a)*	*Composite reliability (rho_c)*	*Average variance extracted (AVE)*
Perceived social presence	0.889	0.890	0.918	0.692
Perceived attractiveness	0.913	0.922	0.935	0.744
Perceived ease of use	0.944	0.947	0.958	0.819
Perceived enjoyment	0.883	0.918	0.917	0.695
Perceived liking	0.897	0.898	0.924	0.708
Perceived usefulness	0.935	0.939	0.951	0.794
Continuous use intentions	0.834	0.836	0.882	0.601

Table 2: Discriminant validity and variance inflation factor

	Perceived attractiveness	*Perceived enjoyment*	*Perceived ease of use*	*Continuous use intentions*	*Perceived liking*	*Perceived usefulness*
Perceived attractiveness		(1.480)			(1.480)	
Perceived enjoyment	0.567			(2.070)		(2.009)
Perceived ease of use	0.568	0.642 (1.506)		(1.783)	(1.506)	
Continuous use intentions	0.411	0.662	0.600			
Perceived liking	0.765	0.767	0.657	0.567		(2.009)
Perceived usefulness	0.495	0.713	0.662	0.677 (2.091)	0.615	
Perceived social presence	0.536	0.525 (1.434)	0.556	0.372	0.441 (1.434)	0.509

Note: the VIF values are shown in brackets.

Table 3: Path coefficients and effect sizes

Hypotheses	*Original sample*	*p-values*	*Effect size*	*Support*
Social presence-> enjoyment	0.175	0.020	0.039	Yes
Social presence-> liking	-0.010	0.924	0.000	No
Attractiveness-> enjoyment	0.234	0.023	0.065	Yes
Attractiveness -> liking	0.519	0.000	0.400	Yes
Ease of use-> enjoyment	0.400	0.000	0.198	Yes
Ease of use -> liking	0.333	0.001	0.166	Yes
Ease of use -> continuous use intentions	0.194	0.046	0.198	Yes
Enjoyment-> continuous use intentions	0.294	0.003	0.088	Yes
Enjoyment -> usefulness	0.551	0.000	0.265	Yes
Liking -> usefulness	0.178	0.316	0.031	No
Usefulness -> continuous use intentions	0.311	0.020	0.086	Yes

Figure 2 shows that the endogenous variables explain 46.8% of the variance in continuous intention to use. This confirms that the predictive power of the model is close to strong. The analysis further recorded the variance explained in perceived enjoyment (44.7%), perceived usefulness (46.0%), and perceived liking (54.6%) as moderate and strong, respectively.

Moreover, the significance of path coefficients (β) was assessed with a maximum *p-value* (p) of 0.05 and Cohen's effect size (f^2). Cohen [84] suggests that the effect of a construct on another can be irrelevant ($f^2<0.02$), weak ($f^2>=0.02$), moderate ($f^2>=0.15$), or strong ($f^2>=0.35$). Figure 2 summarizes the estimated (structural) model. From the results in Table 3, 9 out of the 11 hypothesized relationships were supported. Perceived social presence had a significant and weak effect on perceived enjoyment ($p < 0.05$; $f^2 = 0.039$) but was not significant on perceived liking ($p > 0.05$; $f^2 = 0.000$). Perceived attractiveness also weakly affected both perceived enjoyment ($p < 0.05$; $f^2 = 0.065$) but had a strong effect on perceived liking ($p < 0.001$; $f^2 = 0.400$). Perceived ease of use also had moderate effects on both perceived enjoyment ($p < 0.001$; $f^2 = 0.198$), perceived liking ($p < 0.001$; $f^2 = 0.166$), and a weak effect on continuous use intentions ($p < 0.01$; $f^2 = 0.045$). The results also showed that perceived enjoyment has a moderate effect on perceived usefulness ($p < 0.01$; $f^2 = 0.265$) and a weak effect on continuous use intentions ($p < 0.01$; $f^2 = 0.088$). Finally, the effect of perceived liking on perceived usefulness ($p > 0.05$; $f^2 = 0.031$) and that of perceived usefulness on continuous use intentions ($p > 0.05$; $f^2 = 0.086$) were all weak.

Discussion

Health chatbots are increasingly becoming integral tools in healthcare. They offer a range of services, from providing medical information to supporting patient management. Extant studies have thus investigated the factors that promote health chatbot adoption, acceptance, and/or use. Many of these studies have performed these investigations using traditional technology acceptance, which predominately focuses on utilitarian factors. Meanwhile, studies from other domains have shown that other factors, particularly human-social characteristics of chatbots, can influence their use. These existing studies have also drawn samples from developed communities, leaving out developing societies. However, research shows that factors that inform technology use may differ across different societies. Therefore, this study investigated how human-social characteristics affect users' perceptions of health chatbots using respondents from Africa. This study extended the technology acceptance model (TAM) by incorporating four (4) additional constructs—perceived social presence, perceived attractiveness, perceived enjoyment, and perceived liking—alongside the primary factors of perceived usefulness and perceived ease of use to explain users' continuous use intentions. The PLS-SEM analysis showed that nine (9) out of the eleven (11) proposed relationships were supported. The research model also explained 46.8% of the variance in continuous intention to use.

Future Work and Conclusion

This current study highlights the importance of affective and functional aspects in driving user engagement with technology. The study confirms that human-social characteristics are significant factors in explaining the continuous use intentions of health chatbots. Specifically, the study reveals that perceived enjoyment, perceived ease of use, and perceived usefulness are significant determinants of continuous use intentions of health chatbots. Most importantly, it shows that perceptions of social presence, attractiveness, and ease of use can influence user enjoyment and liking of health chatbots. These findings emphasize the need for developers and designers to prioritize both enjoyable user experiences and practical utility in health chatbot designs.

Although this study provides insightful results, future studies could expand the current scope. Future research could continue to explore additional factors influencing continuous use intentions and consider various contexts and methods to gain a deeper understanding of user behavior. Such insights will be invaluable in developing health chatbots that not only meet immediate user needs but also sustain engagement over time, ultimately contributing to their success and adoption.

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