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OPEN FORUM

What factors predict user acceptance of ChatGPT for mental and physical healthcare: an extended technology acceptance model framework

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Abstract
The rise of ChatGPT has emphasized the need for an improved conceptual understanding of users' agency when interacting with artificial intelligence (AI) systems for healthcare. Australian ChatGPT users ($N=216$) completed a repeated measures online survey. Hierarchical regression analyses assessed the influence of demographic factors (age and gender), Technology Acceptance Model constructs (perceived usefulness and perceived ease of use), and extended variables (trust, privacy concerns) on users' behavioral intentions to use ChatGPT for physical and mental healthcare. The proposed model was partially supported: the findings emphasized the need to establish user trust in ChatGPT and its perceived usefulness in both areas of healthcare. Privacy concerns were a significant predictor of intentions to use ChatGPT for mental healthcare with perceived ease of use predicting intentions to use ChatGPT for physical healthcare. The findings indicate predictors of uses of AI cannot be generalized across healthcare types and unique drivers should be considered.

Keywords AI · ChatGPT · Large language models · Psychosocial models · Technology acceptance

1 Introduction

The healthcare industry is adopting big data analysis using artificial intelligence (AI) to inform and manage healthcare services (Cong-Lem et al. 2024; Hamamoto 2021). AI-assisted services offer the potential for increased care to communities unable to access healthcare services due to factors such as time, distance, stigma, and cost (Reihl et al. 2015). Furthermore, AI relieves the pressure from traditional healthcare providers, many of which are underfunded and fragmented (Occhipinti et al. 2021; Vaidyam et al. 2019). The ability for individuals to gain health information and support from online sources also creates great data sources for public health authorities and researchers to predict, prevent, and treat trending issues (Liu et al. 2023). From a user perspective, it is reasonable to assume that AI devices will become an outlet for seeking medical advice online (Adelstein et al. 2024). However, few studies have focused on what factors drive individuals' intentions to use AI technology for healthcare services.

The release of ChatGPT by OpenAI in late 2022 exposed millions of users to the benefits of adopting AI across disciplines and industries (Roose 2023). ChatGPT is a large language model (LLM) that can comprehend and generate human-like text across various topics and domains due to extensive training on public and personal data, most of which are user-generated (Carlini et al. 2021; Villalobos et al. 2022). ChatGPT is the most widely recognized and used generative AI product, with approximately 50% of the online population having heard of it (Fletcher and Nielsen 2024). It has been reported that ChatGPT hosts 200 million users weekly (Roth 2024). Web users contribute to the production and refinement of LLMs as their online activities (e.g., web browsing, online maps, and app usage) produce data that train AI (Sloane et al. 2022). Furthermore, ChatGPT retains and trains itself on users' conversations (Io and Lee 2017). User data, in turn, give OpenAI an edge in training its models. As such, there is a give-and-take between AI and users as AI development depends on humans in both the training and end-use of the systems (Anderson and Fort 2022). However, this dependency on data input limits ChatGPT's reliability and accuracy (Choudhury et al. 2024).

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Despite being a generalized chatbot designed for conversational assistance, ChatGPT is currently generating the most interest in healthcare research compared to other LLMs (e.g., Google's Gemini; Sallam 2023; Thirunavukarasu et al. 2023). This re-contextualization of intended purposes carries inherent risks for users (Choudhury et al. 2024; Issa et al. 2024). Due to its reliance on inputted data, ChatGPT is at the liberty of its data sources, which may vary from correct to erroneous on any given topic. ChatGPT has been shown to underperform in complex fields such as mental healthcare and can yield biased results that can harm users (Hua et al. 2024). Additionally, there are legitimate concerns related to the misuse of ChatGPT and the confidentiality and security risks of users' personal information (Blanchard et al. 2023; Sallam 2023; Shorey et al. 2024). Therefore, there is some uncertainty around people's intentions to use AI technologies due to influence of risk and fear (Cugurullo and Acheampong 2023). As health data are some of the most private information individuals can share, it is of interest to understand how ChatGPT users perceive it within a healthcare context.

The rapid application and the amplification of AI has emphasized the need for an improved conceptual understanding of the agency users have when interacting with AI systems (Capel and Brereton 2023; Ma et al. 2023). Despite its shortcomings, ChatGPT has emerged as a beneficial technology in healthcare. It is, therefore, essential to understand how users perceive and intend to use ChatGPT. Facilitating an understanding of what factors predict an individual's use of ChatGPT for healthcare can help stakeholders design, update, and market their products to optimize use behavior. As behavioral intentions to use a device are directly related to actual use behavior (Davis 1989; Gansser and Reich 2021), increased use of ChatGPT will benefit OpenAI via training data. As such, the current study aims to offer a preliminary exploration of demographic factors (i.e., age and gender), the technical design features (i.e., perceived usefulness and perceived ease of use), and the sociotechnical factors (i.e., trust and privacy concerns) that drive the people's intentions to use ChatGPT for healthcare.

1.1 E-Healthcare

As access to face-to-face health treatment is problematic for some individuals due to cost, accessibility, and stigma, electronic health (e-health) systems have risen in popularity over the past decade to deliver care through digital means, such as computers and smart phones (Thabrew et al. 2018). E-health tools have been effective for treating anxiety and depression (Fitzpatrick et al. 2017) as well as addressing physical healthcare concerns (Xiao et al. 2024). While specific e-health systems exist for mental and physical health services (see: Wysa, Replika, IBM Watson Health), this study was interested in assessing users' intentions to use a generalized AI chatbot to seek healthcare. The heightened use and the popularity of ChatGPT, compared to less frequently used healthcare chatbots, will likely result in increased data on health topics, resulting in better assistance of people's health needs. Thus, it is timely to research people's intentions to use ChatGPT for healthcare purposes. Furthermore, due to the inconsistencies in engagement across other apps, ChatGPT is a more viable option to ensure user knowledge (Wilks et al. 2021).

This study sought to research health-seeking behaviors through a theoretical technology acceptance framework to better understand what drives individuals' intentions to use AI for their healthcare. Although prior work has similarly used acceptance models, such as Unified Theory of Acceptance and Use of Technology to measure users' behavioral intentions to use e-health systems (Floruss and Vahlpahl 2020; Ngusie et al., 2024; Wilson et al. 2021), specific applications (i.e., ChatGPT) were not referenced. This information can be used to inform future empirical research as well as the development of AI systems seeking to increase use behavior.

1.2 Physical and mental health

One important consideration in the context of health is the distinction between physical and mental healthcare. Prior research has divided physical and mental health into two separate categories (Link et al. 2017; Needham and Hill 2010). While physical health refers to matters of the body (e.g., musculoskeletal), mental health can refer to issues of the mind (e.g., psychological and behavioural; Kendell 2001; World Health Organisation 2022b, c). Literature has found mental health to be more stigmatized than physical health (Kendell 2001; Werner 2015) and that people perceive the risks of AI in psychology as higher than in medicine (Schwesig et al. 2023). Additionally, evidence suggests that there are greater barriers to accessing mental healthcare in comparison with physical healthcare (Henderson et al. 2013). However, many individuals report experiencing challenges accessing physical healthcare (Tabvuma et al. 2022). Challenges, including cost of care, prioritization of mental healthcare over physical healthcare, separation of mental and physical health services, and stigma have been shown to disempower people from engaging in health services (Tabvuma et al. 2022). As such, it is of interest to determine what differences, if any, separate mental and physical health-seeking behaviors.

Despite the expansion of e-health technology and research interest in this field, much of the extant research has focused on physical conditions, with the use of the term "mental" in searches for "electronic personal health record" reducing the available records (Ennis et al. 2011). In fact, the term "mental" is used as an exclusion criterion in the majority of e-health studies (Ennis et al. 2011). Thus, more work is needed to research mental healthcare and explore perceived differences between the two types of health service.

1.2.1 AI in physical healthcare

In light of the COVID-19 pandemic, the health impacts of climate change, the aging population, and the prevalence of chronic health conditions, there is a need to increase the efficiency of healthcare systems to collate detailed data, provide early diagnosis, and create health surveillance systems (Boyd et al. 2022; Goldacre et al. 2022). Through the ability to generate human-like text and directly reply to queries, LLMs such as ChatGPT can improve patient understanding, assist medical staff in optimizing services and procedures, and offer advice (Javaid et al. 2023). In physical healthcare, ChatGPT has been found to correctly diagnose non-melanoma skin cancer and malignant melanomas in 81.8% of cases (Rundle et al. 2024) and deliver consistent and correct responses in 71% of cardiology cases (Monroe et al. 2024). ChatGPT can also pass medical tests (Nori et al. 2023) and provide clinical notes (Giorgi et al. 2023). From a user perspective, ChatGPT can provide information, offer advice, and answer medical questions, providing valuable and accessible healthcare services for many.

Despite the opportunities for AI in e-healthcare, public sentiment is mixed. Rojahn et al. (2023) found that the American general public "strongly" preferred human medical practitioners compared to AI chatbots and felt less comfortable with AI accessing their medical data than a human practitioner. Such low public intention to adopt AI by users reduces the chance of success of AI due to disuse. Another study analyzed 936 American participants' perceptions of AI in healthcare via an online study (Antes et al. 2021). Participants were most open to using technology when monitoring for the risk of a heart attack and least open to a mental healthcare app and a facial-pain monitoring system (Antes et al. 2021). It may be that the latter two scenarios seemed more invasive to the participants, thus requiring more trust in the technology. This point highlights the need to distinguish between users' decision making in physical and mental health contexts.

1.2.2 AI in mental healthcare

Utilizing large quantities of data and enormous computing power, AI technologies are poised to advance mental health practices and research (D'Alfonso 2020). In 2019, one in eight, or 970 million people around the world, were living with a mental disorder, highlighting the necessity for improved accessibility to care (Thieme et al. 2020; World Health Organisation 2022a). As a large portion of mental health issues and their management occur within language (Hua et al. 2024) and accessing care comes with barriers, such as high costs and stigma (Prins et al. 2011), LLMs offer practical solutions to mental healthcare management. Abd-Alrazaq et al. (2019) found that 41 unique chatbots could be used for mental healthcare. These chatbots were namely used for therapy, training, and screening and most commonly treated depression and autism (Abd-Alrazaq et al. 2019). One such chatbot, Wysa, offers a mood tracker, a depression test, and mindfulness activities to combat negative moods (Denecke et al. 2021). Two-third of Wysa users perceived the app as positive and frequent users reported a significant increase in mood compared to occasional users (Inkster et al. 2018). Therefore, LLMs (e.g., chatbots) can assist in treating mental health problems. However, less is known about people's perceptions of using generalized chatbots (e.g., ChatGPT) for mental healthcare services.

While there are positive benefits of AI use for healthcare services, mental health data may be some of the most personal information one can reveal due to its profound connection to an individual's thoughts and emotions, as well as the stigma around many mental illnesses (Thieme et al. 2020). Eyre et al. (2016) suggest that mental health captures more information than any healthcare field. Therefore, mental health clinicians require high trust from their patients due to the nature of their highly confidential conversations (Doraiswamy et al. 2019). However, technology companies do not command the same level of public trust as healthcare professionals (Roy Morgan 2023). Additionally, researchers have found mental health recommendations provided by ChatGPT to be inappropriate and somewhat dangerous for users, threatening their safety (Dergaa et al. 2024). To advance healthcare systems, high-quality data from users are needed to gain insights and train future models (Farah et al. 2023). However, security over personal information is a prominent challenge of using LLMs as they memorize users' interactions and mental healthcare apps do not proactively protect users' data (Mozilla 2022). Therefore, people's decision making should be proactively examined to understand users' perceptions and predictors of sharing their mental health information with AI. Furthermore, few studies have compared people's plans to use ChatGPT between physical and mental health scenarios. As such, this study aims to compare physical health and medical health services to understand individuals' behavioral intentions comprehensively. The Technology Acceptance Model is a commonly employed framework to assess users' decision making.

1.3 Technology acceptance model

Various theories have been developed and deployed to assess the behavioral determinants of user acceptance of advanced technologies. For instance, theories, such as the Theory of

Planned Behaviour (TPB; Ajzen 1991), the Technology Acceptance Model (TAM; Davis 1986; Davis et al. 1989), and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al. 2003), have each been used to predict user adoption of AI systems (Andrews et al. 2021; Gao and Huang 2019; Mohr and Kühl 2021). For instance, Gao and Huang (2019) expanded the TAM with additional predictors such as user experience type to predict intentions to purchase an AI television. The authors stated that it is crucial to add extension variables to the existing TAM framework to expand the generalizability of the model in a specific context. Further, some authors have merged traditional technology acceptance models to further adapt their prediction models. Acheampong and Cugurullo (2019) combined four existing models of technology adoption and diffusion (i.e., TPB, Socio-ecological Model of Behaviour, TAM, Technology Diffusion Theory) to measure adoption of autonomous vehicles (AVs). By merging elements borrowed from previous acceptance models, Acheampong and Cugurullo (2019) were able to recommend models depending on the outcome objective (i.e., adoption intentions, AV-sharing services preference, AV public transport services preference) for autonomous vehicles. Further, and fitting with the traditional models, they found that users' subjective norms (i.e., perception of approval from others) predict their perceived benefits of AVs. Similarly, Oviedo-Trespalacios et al. (2020) evaluated driver acceptance of technology that reduces the use of mobile phones while driving using TAM, TPB, and UTAUT. The authors found that the TAM performed the best in explaining the participants' behavioral intentions when compared to TPB and UTAUT. This finding is consistent with a recent systematic review conducted by Kelly et al. (2023a, b) that reviewed 60 papers on user acceptance of AI systems across a range of industries (e.g., education, accounting, health) and concluded that the TAM had the most predictive success in measuring behavioral intentions in users when compared to other user acceptance models.

Past researches that have utilized TAM to measure healthcare acceptance behaviors have frequently extended the model to include additional factors, such as privacy concerns, trust, and demographics (Kelly et al. 2023a, b; Liu and Tao 2022; Zarifis et al. 2021). This is due to the heterogeneity of AI applications and the rapid development of intelligent technologies since the conception (Koenig 2024). Further, focus on the TAM often assumes active involvement from users (Koenig 2024). This is fitting with research exploring users' decisions to use ChatGPT for healthcare, which requires an active choice to accept and use the technology. As such, it is fitting to apply an extended TAM (eTAM) to predict participants' behavioral intentions to use ChatGPT for physical and mental health services**.**

Behavioral research suggests that individuals' actual use of technology is driven by their perceptions and beliefs (Ajzen and Fishbein 1975; Davis 1986). For instance, the TAM (Davis 1986; Davis et al. 1989) posits that perceived usefulness (PU) and perceived ease of use (PEOU) of technological design factors influence behavioral intentions, which, in turn, predicts behavioral (actual) use (Alhashmi et al. 2020). PU indicates the extent to which an individual perceives technology as valuable in their life and it frequently serves as a strong predictor of technology acceptance (Davis 1986; Gao and Huang 2019). PEOU is the individual's measure of how difficult the technology would be to use. PEOU has been reported to be a significant positive predictor of behavioral intentions albeit with a lesser impact than PU (Davis 1986; Zhang et al. 2021). Prior research has revealed that the conversational ability of an e-health chatbot increased useability and acceptability of the app (Malik et al. 2022). As such, LLMs like ChatGPT may be perceived as easy to use due to their design. Behavioral intention represents an individual's willingness and readiness to engage in a specific behavior and is strongly linked to the actual use of technology (Davis 1986; Davis et al. 1989), such as ChatGPT (Strzelecki 2023). The TAM model was used in this research to study users' acceptance of ChatGPT for seeking mental and physical health advice. Although the TAM covers the technical constructs of PU and PEOU, it was devised as a generic model of technology acceptance before the increasing sociotechnical concerns surrounding user privacy.

1.3.1 Privacy concerns

AI devices that utilize individuals' personal data face potential privacy issues due to the invisible ways AI models use data (Stahl and Wright 2018) and inadequate security (Pool et al. 2024). For instance, health information contains data points that allow the user to be easily identifiable (Raskar et al. 2020). Consequently, there is a trade-off between use behavior and privacy when using technology for healthcare services (Dinev and Hart 2006b). Prior studies demonstrate that users' privacy concerns negatively predict their behavioral intentions to adopt a technology (Huang et al. 2022; Kelly et al. 2023a, b; Park and Shin 2020). For instance, Dhagarra et al. (2020) extended the TAM to include privacy concerns and trust and found that both of these predictors significantly influenced the acceptance of healthcare technology among Indian healthcare recipients. Specifically, privacy concerns significantly and negatively influenced individuals' behavioral intentions. Another study found that patients were most influenced by privacy concerns when deciding to share their health information compared with other predictors such as patient–physician relationship (Abdelhamid et al. 2017). In contrast, privacy concerns did not significantly predict participants' usage of ChatGPT in Menon and Shilpa (2023) study. The authors noted that this finding may be due to the perceived benefits gained from using ChatGPT. However, as Menon and Shilpa's (2023) study was not specific to healthcare, more research is required to understand if the same trade-off is perceived for healthcare use.

There is a conflict between the professional need for healthcare data and patients desire to conceal both physical and mental health data (Ivanova et al. 2020). As disclosing personal information is the basis for medical treatment, exploring users' privacy concerns and how this influences the intention to seek health information from ChatGPT is essential. While prior work has studied the effects of health information privacy concerns on intentions to use AI technology (Kelly et al. 2022; Liu and Tao 2022; Zhang et al. 2018), this paper adds to the current literature by studying the influence of privacy concerns on using AI in differing health scenarios. While privacy concerns predict refraining from posting identifiable information online, trust encourages disclosing identifiable information (Mesch 2012). Consequently, privacy concerns and trust inversely predict behavioral intentions to use AI.

1.3.2 Trust

To build AI-based systems that users can trust, the trustworthiness of AI systems must be understood (Toreini et al. 2020). Since the origin of the TAM, various researchers have extended and varied the model to capture the behavioral determinants of technology acceptance (e.g., Unified Theory of Acceptance and Use of Technology, Theory of Planned Behaviour, and AI Device Use Model; Schmidt et al. 2020). Trust is often found to be the strongest significant positive predictor of willingness to provide data to AI when included alongside the standard TAM variables (Kelly et al. 2023a, b). Therefore, as trust increases, so do users' technology acceptance of AI (Gefen et al. 2003; Kelly et al. 2023a, b). Despite the continued presence of trust in technology acceptance research, trust is not included in any original models that measure technology acceptance. Furthermore, the majority of AI trust research has been conducted before the emergence of accessible, intelligent devices, such as ChatGPT (Alvarado 2022; Boehm et al. 2022; Schmidt et al. 2020). Bahtiyar and Çağlayan (2014) state that the perceived trustworthiness of e-health systems depends on the subjective needs of the person and the independent security of each system. As such, trust may differ between traditional health systems and AI devices like ChatGPT. Further work is required to examine how trust is interrelated with specific AI applications, user characteristics, and technical features (Sousa et al. 2024).

Context is a key factor of trust in AI systems (Bach et al. 2022). When using ChatGPT for health information, users must trust big technology firms with their data (i.e., OpenAI). However, technology companies often elicit lower user trust than health institutions. The Centre for Data Ethics and Innovation (2022) found the majority of British adults trusted the National Health Service (NHS) the most (74%) to safely handle their data. Meanwhile, a lower share of people reported trust in big technology companies (43%) to handle their data safely, effectively, and transparently. This finding fits with other research, such as Platt and Kardia (2015) who studied 447 participants' trust in health information sharing. They found that knowledge, privacy, benefits, psychosocial factors, and experience influence trust evaluations in health information systems (e.g., biobanks and electronic health records). As such, the literature points to a trust deficit between individuals and the companies collecting, aggregating, and sharing or selling their data (Flanagan and Warren 2024).

Alternatively, Choudhury et al. (2024) asked 607 American participants to respond to the statement 'ChatGPT is trustworthy' on a 4-point Likert scale (1 = strongly disagree to 4 = strongly agree). Trustworthiness had a mean score of 3.17, indicating that participants 'somewhat agreed' that ChatGPT was trustworthy (Choudhury et al. 2024). However, Choudhury et al. (2024) did not measure trust in ChatGPT for health-specific tasks and reported that only 44 participants (7.3%) had used ChatGPT for health-related queries. Further research is required to assess the role of trust in users' intentions to use AI for health-specific services.

2 Research gap

It is essential to proactively research and amplify the voices of stakeholders (i.e., ChatGPT users) to understand what drives individuals to disclose their personal information to AI to inform policy, research, and development (Yoo et al. 2024). As per the Socio-Technical Systems Theory, the individual, the organization, and the technology must be given equal consideration before the introduction of a new technology (Sittig and Singh 2010). However, these goals may not always be consistent with each other. While technology pundits and AI developers have flooded the discourse around ChatGPT, human-centered research has received less attention. Research is required to understand stakeholders' perceptions of AI in a healthcare context so that devices like ChatGPT reflect the opinions and the attitudes of the users who are affected by their outcomes (Capel and Brereton 2023; Groves 2022; Shneiderman 2022). Capel and Brereton (2023) noted that most papers researching AI in healthcare studied clinical specialists as the end-users rather than prospective or actual patients. Sharevski et al. (2023) echoed this observation, stating that LLMs are currently only evaluated by experts without verifying how ordinary users assess, engage, and use this technology for medical advice. Healthcare was selected as the focus of the current study due to the increased interest in using AI in this field (Antes et al. 2021; Cong-Lem et al. 2024; Kwak et al. 2022; Zack et al. 2023). The opportunity to pinpoint behavioral intentions during a period of heightened interest and use of ChatGPT in healthcare (Moulaei et al. 2024) provided the chance to identify what factors drive an individual's intentions to disclose health information to AI. As such, the current paper seeks to identify the predictors of behavioral intentions of ChatGPT users to assist with providing recommendations to inform future developments in AI.

2.1 Current study

Technology acceptance research is important to aid safe development and use of systems that will add instrumental values to medical research and care. While prior work has measured users' intentions to use ChatGPT for health-related services (Shahsavar and Choudhury 2023), the exclusion of trust, privacy concerns, and demographic factors creates a gap in the literature that should be addressed. Furthermore, the extant literature has not compared intentions between mental and physical healthcare scenarios. Guided by previous work (Kelly et al. 2022; Panagoulias et al. 2024), the current study employed an extended TAM (eTAM) to predict participants' behavioral intentions to use ChatGPT for physical and mental health services. The following aims and hypotheses were formed to structure the study:

Research Aim 1: Test the utility of an eTAM to predict users' behavioral intentions to use ChatGPT for mental and physical healthcare.

Hypothesis 1: Consistent with the TAM, PU and PEOU would significantly positively predict behavioral intentions to use AI chatbots in both mental and physical health scenarios.

Hypothesis 2: For the additional constructs, privacy concerns would significantly negatively predict behavioral intentions to use AI chatbots in both mental and physical health scenarios, above and beyond the TAM predictors of PU and PEOU. Trust would significantly positively predict behavioral intentions to use AI chatbots in both mental and physical health scenarios, above and beyond the TAM predictors of PU and PEOU.

Research Aim 2: Compare the importance of the eTAM constructs for physical and mental healthcare.

In an exploratory manner, any differences in the patterns of the TAM constructs (PU, PEOU) and additional variables (trust, privacy concerns) predicting intentions for physical and mental healthcare will be identified as will any mean differences in the eTAM constructs between the healthcare scenarios.

3 Methodology

3.1 Participants and recruitment

We recruited a convenience sample of 216 participants aged 18–77 years (*M* age = 26.51 years, *SD* = 11.24) from the Australian population. Participants were recruited through an online university student research management system (SONA) and received 0.5-course credit for survey completion. Participants were also recruited from the general population and were invited to enter a prize draw with the chance to win one of six $50 (AUD) gift vouchers. Recruitment was conducted online and via word of mouth, with the online survey open from August 2023 to March 2024. Demographic factors are presented in Table 1. Of note, just over half had knowledge that ChatGPT collects information and most did not know that they could turn off their chat history.

3.2 Measures

3.2.1 Technology acceptance model

A 7-point Likert Scale (1 = *Strongly disagree*, 7 = *Strongly agree*) was used to assess all variables within the eTAM. Participants were asked to indicate how much they "agree or disagree with the following statements regarding using ChatGPT for physical health advice". Four items measured PU, "Using ChatGPT would be useful", "Using ChatGPT would improve my productivity", "Using ChatGPT would enhance my effectiveness," and "Using ChatGPT would allow me to seek advice quickly" (Davis 1986; Silva et al. 2023). Four items represented PEOU, "I believe I would find ChatGPT clear and understandable to use", "I believe interacting with ChatGPT would not require a lot of mental effort", "I believe I would find ChatGPT to be easy to use", and "I believe I would find it easy to get ChatGPT to provide me with the advice I am looking for" (Davis 1986; Silva et al. 2023). Three questions measured behavioral intention, "In the next two weeks, I plan to use ChatGPT to seek physical health advice", "In the next two weeks, I would recommend using ChatGPT to seek physical health advice to someone close to me", and "I believe my interest in using ChatGPT to seek physical health advice will increase over the next two weeks" (Davis 1986; Silva et al. 2023). All questions were repeated for the mental health scenario.

3.2.2 Privacy concerns

Participants were asked to indicate how much they "agree or disagree with the following statements regarding using ChatGPT for physical health advice". Three items were adapted

Table 1 Demographic frequencies of the study sample

	N	%
Gender		
Females	162	75.0%
Males	47	21.8%
Non-binary	4	1.9%
Transgender	1	0.5%
Prefer not to say	1	0.5%
Race		
White Australian	140	65.8%
Asian	32	14.8%
Multiple races	12	5.6%
Australian Aboriginal, South Sea Islander, Torres Strait Islander or Norfolk Islander	8	3.7%
Asian Indian	8	3.7%
Hispanic	5	2.3%
Prefer not to say	6	2.8%
Other	5	2.3%
Sexual orientation		
Straight	152	70.4%
Bisexual	25	11.6%
Homosexual	14	6.5%
Pansexual	12	6.0%
Asexual	4	1.9%
Other	1	0.5%
Prefer not to say	7	3.2%
Monthly income		
Nil income	11	5.1%
$1–$799	32	5.1%
$800–$1999	62	28.5%
$2000 or more	96	44.4%
Prefer not to say	21	9.7%
Education		
Year 11 or below	6	2.7%
Year 12	109	48.7%
Bachelor degree	54	24.1%
Advanced diploma or diploma	21	9.4%
Postgraduate degree	34	15.2%
*Pre-existing knowledge**		
Yes	114	52.8%
No	92	42.6%
Unsure	10	4.6%
*Chat history***		
Yes	10	4.6%
No	49	22.7%
I did not know this was an option	140	64.8%
Manually delete certain conversations, but not all of them	17	7.9%
*Prior use****		
Creative fun	47	21.8%
To research	79	36.6%
Editing and/or reviewing writing	50	23.1%
To write code	9	4.2%
For self-interest (e.g., cooking advice)	45	20.8%
For safety advice	6	2.8%
For health information	23	10.6%
To translate text to another language	11	5.1%
To write emails	27	12.5%
Work-related tasks	21	9.7%

*Pre-existing knowledge represents the item, "Before today, did you know that ChatGPT collects and uses the information you enter into the conversation for training, which informs its answers in future?"

**Chat history represents the item, "When using ChatGPT, do you turn off your chat history?"

***Prior use represents the item, "What have you used ChatGPT for in the past two weeks? You can select multiple answers"

from Dinev and Hart (2006a) to measure participants' privacy concerns, "I am concerned that the information I share with ChatGPT to assist with finding information about my physical health concern could be misused", "The consequences of an information breach due to me using ChatGPT to assist with finding information about my physical health concern are likely to be very serious", and "It would be risky for me to use ChatGPT to assist with finding information about my mental/physical health concern." All questions were repeated for the mental health scenario.

3.2.3 Trust

Participants were asked to indicate how much they "agree or disagree with the following statements regarding using ChatGPT for physical health advice". Six items measured trust, "ChatGPT would be dependable for assisting with finding information about my physical health concern," "ChatGPT would be reliable for assisting with my search for information about my physical health concern" (Liu and Tao 2022), "ChatGPT would be honest when assisting with my information search for my physical/mental health concern", "ChatGPT would care about me when assisting with my information search for my physical/mental health concern", "ChatGPT would provide a favorable service when assisting with finding information about my physical/mental health concern", and "ChatGPT would be trustworthy when assisting in finding information about my physical/mental health concern" (Zhang et al. 2021). All questions were repeated for the mental health scenario.

3.3 Procedure

This study was approved by the Queensland University of Technology (QUT) Ethics Committee (approval number:

6926). Participants were recruited via social media, including Facebook, Instagram, LinkedIn, and an online university student research management system (SONA). After obtaining participants' informed consent and ensuring they met the eligibility criteria (i.e., 18 years or older, currently residing in Australia, and having used ChatGPT at least once before), participants were directed to complete the online survey. The survey first asked for participants' demographic information (e.g., age and gender). They were then provided with a definition of AI that has been used in past works ("An unnatural object or entity that possesses the ability and capacity to meet or exceed the requirements of the task it is assigned when considering cultural and demographic circumstances"; Bringsjord 2011; Dobrev 2012; Kelly et al. 2023a, b; McLean and Osei-Frimpong 2019; Omohundro 2014) and ChatGPT ("An AI language model that generates human-like text based on the input provided by the user. The training data comes from a diverse range of texts on the internet. When you input your data into ChatGPT, it collects and stores the information to train future versions of this technology"; OpenAI 2024). They were asked about their pre-existing knowledge and use behavior of ChatGPT.

Next, participants read either the mental or physical health scenario. The order of scenarios was randomized to control for order and fatigue effects. For the physical health condition, participants were shown a definition of physical health (i.e., "The overall state of the body that encompasses both the internal and external aspects of the body, including organ function, cardiovascular health, and musculoskeletal integrity, among others"; World Health Organisation 2022c). Likewise, in the mental health condition, they were provided a definition of mental health (i.e., "A person's overall psychological well-being, including their emotional, cognitive, and behavioral state. It encompasses how people think, feel, and behave and how they cope with stress, interact with others, and make decisions"; World Health Organisation 2022b). The definitions were accompanied by example scenarios that briefly described circumstances that may prompt them to seek health advice from ChatGPT, such as a knee injury or feeling down. Participants completed the eTAM measures concerning the presented healthcare scenario, with scales that measured their PU, PEOU, trust, and privacy concerns. The online survey was open from August 2023 to March 2024.

3.4 Data analyses

The Statistical Package for the Social Sciences (SPSS) Version 28 was used to conduct all analyses. All significance values were assessed at $p < 0.05$. Bivariate relationships were measured. Two hierarchical regression analyses were used to test the eTAM in both the physical and mental health scenarios (H1 and H2). The choice of hierarchical regression analysis is supported by similar studies that have assessed the distinct influence of TAM predictors in addition to other factors (Kelly et al. 2022; Oviedo-Trespalacios et al. 2020; Teeroovengadum et al. 2017).

For both hierarchical regressions, age and gender were entered into Step 1, TAM factors (PU and PEOU) were entered into Step 2, and trust and privacy concerns were entered into Step 3. To test H3, inspection of the significance of the regression coefficients allowed a comparison of any difference in the pattern of important predictors of intention between physical and mental health scenarios and paired-samples t-tests were conducted to assess if there were significant differences in the mean values of the eTAM constructs between the two healthcare scenarios.

4 Results

4.1 Data analyses

Visual assessment of the residual histograms indicated that data were normally distributed. The residual and pairwise scatterplots confirmed linearity. Skewness and kurtosis values were between the recommended ± 2 (Bowerman and O'Connell 1990). Collinearity tests indicated that the assumption of multicollinearity was met (i.e., VIF > 10, Tolerance < 0.1; Bowerman and O'Connell 1990). The observations were independent.

Table 2 Descriptive and reliability statistics of physical healthcare scales

Scale	*n*	*M (SD)*	*95%* CI	*α*	Range	Skew
PU	216	4.510 (1.353)	[4.34–4.71]	.893	1–7	−0.65
PEOU	216	5.214 (1.020)	[5.10–5.36]	.828	1–7	−0.74
Behavioral intention	216	3.960 (1.630)	[3.76–4.20]	.897	1–7	−0.16
Trust	216	3.833 (1.330)	[3.68–4.03]	.901	1–7	−0.11
Privacy concerns	216	4.653 (1.420)	[4.48–4.90]	.826	1–7	−0.42

n = valid sample size; *M* = mean; *SD* = standard deviation; CI = confidence interval; *α* = Cronbach's alpha. Scales: 1 = strongly disagree, 7 = strongly agree. PU = perceived usefulness. PEOU = perceived ease of use

Table 3 Descriptive and reliability statistics of mental healthcare scales

Scale	*n*	*M* (*SD*)	*95%* CI	*α*	Range	Skew
PU	216	4.180 (1.434)	[4.01–4.40]	.889	1–7	−0.50
PEOU	215	5.020 (1.194)	[4.90–5.20]	.869	1–7	−1.10
Behavioral intention	216	3.773 (1.711)	[3.55–4.02]	.920	1–7	−0.08
Trust	216	3.631 (1.301)	[3.47–3.82]	.892	1–7	0.03
Privacy concerns	216	4.640 (1.430)	[4.45–4.84]	.844	1–7	−0.46

n = valid sample size; M = mean; SD = standard deviation; CI = confidence interval; α = Cronbach's alpha. Scales: 1 = strongly disagree, 7 = strongly agree. PU = perceived usefulness. PEOU = perceived ease of use

4.2 eTAM descriptive statistics

Descriptive statistics of the eTAM for physical health are presented in Table 2 and the descriptive statistics for mental health are presented in Table 3. Both tables show that mean scores ranged between 3.63 and 5.44, and reliability was acceptable for all scales across both conditions. Scores for behavioral intention around the midpoint demonstrate that participants neither agreed nor disagreed that they would use ChatGPT to seek physical or mental health advice in future.

4.3 Bivariate relationships

The bivariate correlations were conducted between the independent and dependent variables (Appendix). Prior to conducting these correlations, gender was converted to a binary item (i.e., female and other). While we recognize more than two genders exist, this categorization was required for predictive analyses. Age was also converted to a binary item (17–25; 62.5% and ages 26–77; 37.5%) due to the relatively young sample (M age = 26.5). For both the physical and mental healthcare scenarios, age and gender were not significantly correlated with behavioral intention. PU, PEOU, and trust were significantly and positively correlated with behavioral intention for physical and mental healthcare. Privacy concerns were significantly and negatively correlated with behavioral intention for physical and mental healthcare.

4.4 Hierarchical regression

Two hierarchical regressions were conducted to measure the predictive power of demographic details (age and gender), the TAM (PU and PEOU), and the two extended variables (trust and privacy concerns) on behavioral intentions to use AI in mental and physical healthcare (Table 4). An a priori power analysis was conducted using G*Power (Faul et al. 2009) to evaluate the sample size for the logistic regression. The observed statistical power was 0.80, α = 0.05 (Beck 2013; Cohen 1988) for a sample of 213 participants, providing evidence for the robustness of the sample size (N = 216).

4.4.1 Physical healthcare

In Step 1, age and gender did not significantly account for any variance in behavioral intentions to use an AI chatbot for physical healthcare, $F(2, 213) = 1.331$, $p = 0.266$. PU and PEOU were entered into Step 2. There was a significant increase in the variance of behavioral intentions, $R^2_{change} = 0.361$, F_{change} (2, 211) = 60.802, $p < 0.001$, and the model became significant, $F(4, 211) = 31.440$, $p < 0.001$. At Step 2, PU and PEOU were both significant positive predictors of behavioral intentions to use AI chatbots for physical healthcare (see Table 4). Further, PU explained the most unique variance in behavioral intentions at this step. Trust and privacy concerns were entered into Step 3 of the hierarchical regression. When trust and privacy concerns were entered into Step 3, the variance of behavioral intentions significantly increased, $R^2_{change} = 0.069$, F_{change} (2, 209) = 12.867, $p < 0.001$, and the model remained significant, $F(6, 209) = 27.607$, $p < 0.001$. At Step 3, PU, PEOU, and trust were all significant positive predictors of intentions. Privacy concerns were not a significant predictor of behavioral intentions. Trust explained the most unique variance in behavioral intentions. The model significantly accounted for 42.6% of the variance in behavioral intentions to use ChatGPT for physical healthcare.

4.4.2 Mental healthcare

In Step 1, age and gender did not significantly account for any variance in behavioral intentions to use an AI chatbot for mental healthcare, $F(2, 213) = 0.186$, $p = 0.830$. PU and PEOU were entered into Step 2. There was a significant increase in the variance of behavioral intentions, $R^2_{change} = 0.396$, F_{change} (2, 211) = 69.396, $p < 0.001$, and the model became significant, $F(4, 211) = 34.851$, $p < 0.001$. At Step 2, PU was a significant positive predictor of behavioral intentions to use AI chatbots for mental healthcare (see Table 4). However, PEOU was not a significant predictor

Table 4 Hierarchical regressions predicting intentions to use ChatGPT for physical and mental healthcare

Step	Physical healthcare							Mental healthcare						
	Adj. R^2	*B*	SE B	Sig	95% CI		β	Adj. R^2	*B*	SE B	Sig	95% CI		β
					Lower bound	Upper bound						Lower bound	Upper bound	
1	.003							−.008						
Age		−0.290	0.229	0.208	−0.741	0.162	−0.086		−0.114	0.242	0.639	−0.591	0.364	−0.032
Gender		−0.714	0.627	0.256	−1.949	0.521	−0.078		−0.285	0.663	0.668	−1.591	1.021	−0.030
2	.362							.386						
Age		−0.146	0.184	0.429	−0.509	0.217	−0.044		−0.017	0.189	0.930	−0.39	0.357	−0.005
Gender		−0.434	0.502	0.388	−1.424	0.556	−0.047		0.362	0.520	0.487	−0.663	1.388	0.038
PU		**0.562**	**0.08**	**<.001**	**0.404**	**0.720**	**0.467**		**0.690**	**0.082**	**<.001**	**0.528**	**0.853**	**0.578**
PEOU		**0.317**	**0.107**	**0.003**	**0.107**	**0.527**	**0.198**		0.118	0.098	0.232	−0.076	0.312	0.082
3	.426							.440						
Age		−0.045	0.177	0.801	−0.393	0.304	−0.013		0.074	0.183	0.685	−0.286	0.434	0.021
Gender		−0.462	0.477	0.334	−1.403	0.478	−0.05		0.283	0.500	0.572	−0.702	1.268	0.029
PU		**0.353**	**0.086**	**<.001**	**0.182**	**0.523**	**0.293**		**0.500**	**0.094**	**<.001**	**0.314**	**0.685**	**0.419**
PEOU		**0.237**	**0.103**	**0.022**	**0.035**	**0.440**	**0.148**		0.091	0.094	0.334	−0.095	0.277	0.064
Trust		**0.389**	**0.082**	**<.001**	**0.227**	**0.550**	**0.317**		**0.320**	**0.093**	**<.001**	**0.137**	**0.504**	**0.244**
Privacy concerns		−0.067	0.062	0.282	−0.190	0.055	−0.058		**−0.154**	**0.063**	**0.015**	**−0.277**	**−0.03**	**−0.128**

Note. $N=216$. B = unstandardized coefficients. SE = standard error, β = standardized coefficients, CI = confidence intervals. PU = perceived usefulness, PEOU = perceived ease of use. Bolded items are significant of behavioral intentions. Trust and privacy concerns were entered into Step 3 of the hierarchical regression. When trust and privacy concerns were entered into Step 3, the variance of behavioral intentions significantly increased, $R^2_{change} = 0.058$, F_{change} (2, 209) = 11.137, $p < 0.001$, and the model remained significant, F(6, 209) = 29.178, $p < 0.001$. At Step 3, PU and trust were significant positive predictors of intentions. Privacy concerns significantly and negatively predicted intentions. PU explained the most unique variance in behavioral intentions. The model significantly accounted for 44% of the variance in behavioral intentions to use ChatGPT for mental healthcare.

4.5 Mean differences between healthcare scenarios

Paired-samples t-tests were conducted to compare group means for each variable in the two healthcare scenarios (physical vs. mental). There was a significant difference in PU in the results for physical health and mental health, $t(218) = 4.21$, $p < 0.001$. Participants had significantly higher mean scores in PU of ChatGPT for physical health ($M = 4.51$, $SD = 1.34$) than mental health ($M = 4.18$, $SD = 1.43$). There was a significant difference in PEOU in the results for physical health and mental health, $t(218) = 3.35$, $p < 0.001$. Participants had significantly higher mean scores in PEOU in relation to ChatGPT for physical health ($M = 5.21$, $SD = 1.01$) than mental health ($M = 5.01$, $SD = 1.19$). There was a significant difference in trust in the results for physical health and mental health, $t(215) = 3.17$, $p < 0.001$. Participants had significantly higher mean scores in trust for ChatGPT for physical health ($M = 3.83$, $SD = 1.33$) than mental health ($M = 3.63$, $SD = 1.30$). There was no significant difference in privacy concerns in the results for physical health ($M = 4.65$, $SD = 1.42$) and mental health ($M = 4.64$, $SD = 1.43$), $t(215) = 0.23$, $p = 0.820$. There was a significant difference in behavioural intentions in the results for physical health and mental health, $t(218) = 2.43$, $p = 0.016$. Participants had significantly higher mean scores in intention to use ChatGPT for physical health ($M = 3.96$, $SD = 1.62$) than mental health ($M = 3.77$, $SD = 1.70$).

5 Discussion

The current study has provided a preliminary framework that establishes the interrelations between user characteristics, sociotechnical factors, and technical design features of ChatGPT to predict behavioral intentions to use ChatGPT in physical and mental healthcare. Additionally, this study highlighted differences in users' intentions to use ChatGPT between physical and mental health scenarios. By recruiting and researching ChatGPT users, this initial examination addresses a gap identified by previous papers by exploring end-user behaviors (Capel and Brereton 2023; Sharevski et al. 2023). Additionally, while other papers segment research regarding the use of ChatGPT for general healthcare (Rojahn et al. 2023) and mental healthcare (Dergaa et al. 2024), this paper combines the two fields to provide a comprehensive overview of differences between user perceptions. Further, by specifying a LLM (i.e., ChatGPT), this paper adds light to other work that has researched AI acceptance more broadly (Lee et al. 2021). As such, this paper can act as a stepping stone to future empirical research.

This initial investigation partially supports the utility of an eTAM in predicting individuals' behavioral intentions to use ChatGPT for physical and mental health services. The findings demonstrated that eTAM variables influenced users' plans to seek physical and mental health services using ChatGPT differently, partially supporting the hypotheses. However, users mean scores demonstrated their moderate attitudes and intentions for using ChatGPT for health advice in future. By applying the same model across two scenarios, we have provided a reference for applying an eTAM in an analysis of current ChatGPT users' acceptance of the technology.

5.1 Factors that predict behavioral intentions to use AI for both physical and mental healthcare

PU significantly and positively predicted behavioral intentions in both the mental and physical health scenarios (H1). Therefore, the more people perceive ChatGPT as useful for seeking health services, the more they are inclined to use the technology. This finding is consistent with prior research demonstrating that PU strongly predicts intentions above and beyond demographic factors (Gado et al. 2021; Kelly et al. 2023a, b). Additionally, PU remained significant in the overall model, demonstrating users' need to feel that the device contributes added value to their lives to use it. However, it is important to note that both mean scores were approximately '4' for PU, demonstrating that participants neither agreed nor disagreed with the usefulness of ChatGPT for health advice. To encourage use, companies such as OpenAI should promote the usefulness of their AI products. In the context of healthcare, companies should promote the ability of AI to reduce barriers like cost, time, and stigma to drive PU (Reihl et al. 2015).

The significance of trust, when entered into the third step of the eTAM, demonstrates that as individuals' trust in ChatGPT increases, so do their intentions to accept and use the LLMs (H2). This finding supports extant literature that has found trust to be a significant predictor of use behavior when included in the eTAM (Liu and Tao 2022; Seo and Lee 2021). However, the approximate means of '4' for trust reveals that users 'neither agreed or disagreed' that ChatGPT is trustworthy for health advice. The participants' neutral trust in ChatGPT for healthcare differs from Choudhury et al.'s (2024) finding that users 'somewhat agreed' that ChatGPT was trustworthy, highlighting the differences between general trust in ChatGPT and trust in ChatGPT for healthcare. Technology companies should promote trust through rigorous product testing to reduce misinformation or disinformation, be transparent about the origin of the information, and provide privacy barriers for users' data (Demartini et al. 2020; Rifon et al. 2005; Sousa et al. 2024). These strategies could improve users' trust in the device's output and data security, which may drive use behavior.

5.2 Factors that predict behavioral intentions to use AI for physical healthcare

In addition to the significant predictors of PU and trust, PEOU was a significant positive predictor of behavioral intentions to use ChatGPT for physical health advice (H1). As the PEOU rises, so do users' intentions to use ChatGPT for physical healthcare. Comparatively, PEOU was not a significant predictor in the mental healthcare scenario. While LLMs have been popularized for mental healthcare (Abd-Alrazaq et al. 2019), specialized LLMs are less commonly found for physical health concerns. Instead, many doctors have adapted to technology via telehealth services. Therefore, participants in the current sample may be less familiar with using LLM to seek physical healthcare, driving the significance of PEOU in the model. Furthermore, as mental healthcare is largely language-driven, LLMs could be perceived as more straightforward to use for this concern in comparison to physical healthcare, which often involves the visualization of a body part (e.g., rash) to diagnose. Of note, only 10.6% reported using ChatGPT for health information in the past fortnight. This finding is similar to Choudhury et al.'s (2024) report that 7.3% of their participants had used ChatGPT for health-related queries. While it may be suggested that the participants were not unwell during this period, it could also be that participants were not familiar with using ChatGPT for healthcare purposes. Consequently, developers should aim to maintain (or increase) the PEOU by designing devices that are simple to use, provide clear instructions, and are responsive to users' issues. Further, developers may wish to implement features that allow feedback to ensure that users' experiences are used to improve the devices' usability over time.

Despite the significance of PEOU in the physical healthcare model, PU was a stronger predictor of intentions to use ChatGPT. This finding aligns with previous research that found PEOU to be less important than PU in the TAM (Davis 1986). Some scholars have suggested that PEOU is less important in technology use due to people's familiarity with using technology in their daily lives (Lunney et al. 2016). As some of the participants were university students, it could be assumed that they felt familiar with using technology. Furthermore, as this population comprised all previous users of ChatGPT, it could be presumed they knew how to use this technology due to past behavior.

5.3 Factors that predict behavioral intentions to use AI for mental healthcare

In addition to the significant predictors of PU and trust, privacy concerns were significantly and negatively predictive of intentions in the mental health scenario (H2). Therefore, the more concern individuals felt for their privacy, the less likely they were to intend to use ChatGPT for their mental healthcare. Although the mean scores were not significantly different for privacy concerns between the two scenarios (see Sect. 4.5), it appears that the effect of privacy concerns on users' behavioral intentions was stronger in the mental health scenario compared to physical healthcare. This finding is supported by prior research that states mental health data are some of the most sensitive data one can reveal due to the stigma and association with life events and additional health issues (Habicht et al. 2024). In comparison, privacy concerns were not a significant predictor in the eTAM for users' intentions to use ChatGPT for mental healthcare. This result may be informed by the finding that 52.8% of participants in the current sample were aware that ChatGPT memorizes their information, while only 4.6% disabled their chat history. Therefore, the limited number of participants opting out of ChatGPT's data collection could heighten their privacy apprehensions as they perceive their data as inadequately safeguarded.

The significance of privacy concerns in the mental healthcare eTAM highlights the need for companies to proactively safeguard users' information. It is recommended that privacy features be made more apparent to users of LLMs, such as ChatGPT, through increased focus on transparency, data literacy, and affirmative (i.e., opt-in) data collection (King and Meinhardt 2024). For example, companies could ask whether a customer's data could be used for training purposes and specify the intended use (King and Meinhardt 2024). Prior research has demonstrated that users will provide their data to AI when they believe it will be socially beneficial and understand the purpose of use (Kelly et al. 2023a, b; Yoo et al. 2024).

While protecting user privacy may not directly benefit LLM training due to limited access to data, it can alleviate privacy concerns, increasing user adoption and engagement. As such, businesses should consider emphasizing data privacy and reassessing any goals related to extended data retention. In some cases, business objectives, such as profitability, may conflict with safety policies and regulations that prioritize user privacy. Additionally, governments should consider placing safety regulations to ensure that user data are not sold or shared between companies, thus protecting user data and reducing privacy concerns. While this research was confined to studying a generalized chatbot, safety and privacy guardrails are pertinent for LLMs that specify in delivering mental health advice (e.g., Wysa) based on the finding that users have significant privacy concerns in the mental health information, compared with the (non-significant) finding for privacy concerns in the physical health scenario.

5.4 Model comparisons

The influence of each independent variable differed across the two health behaviors. As such, the current findings cannot be generalized across industries. For instance, PU explained the most unique variance in intentions to use ChatGPT for mental and physical healthcare in step two of the hierarchical regression, displaying its dominance in the TAM. However, when added to the eTAM, trust was the strongest predictor of intentions to use ChatGPT for physical healthcare. Meanwhile, PU remained the strongest predictor of behavioral intentions to use mental healthcare in the eTAM. This comparison highlights the differential importance of these predictors and underscores the importance of considering specific contextual factors and user perceptions in understanding technology adoption behavior.

The paired-samples t-tests showed that the independent variables significantly differed between mental and physical healthcare. Every variable except for privacy concerns significantly differed between the mental and physical health scenarios (RA2). Specifically, the mean scores for PU, PEOU, trust, and behavioral intentions for ChatGPT were higher in the physical health scenario than in the mental health scenario. Users perceived ChatGPT to be more useful, easier to use, more trustworthy, and had stronger intentions to use ChatGPT for physical healthcare in comparison to mental healthcare. This finding supports prior research that suggests that users' perceptions differ between physical and mental health behaviors (Kendell 2001; Werner 2015). To our knowledge, this is the first study that has shown the difference in users' acceptance of using ChatGPT for physical healthcare compared to mental healthcare. The difference between the two models underscores the need to conduct industry-specific analysis and the importance of including users' perspectives in the design and use of ChatGPT for specific applications, as users' behavior cannot be generalized. It is recommended that future research analyzing multiple industries use this methodology to compare their results.

5.5 Limitations and future recommendations

While this study contributed to the literature by providing novel evidence of users' behavioral intentions to use ChatGPT in two health scenarios, the limitations warrant mention. The recruitment strategy primarily targeted a convenience sample of previous ChatGPT users, potentially limiting the generalizability of findings. Future research should aim to include a broader sample, including new users and those who choose not to use AI, to better understand the factors influencing users' cognitive and emotional responses to AI. Moreover, this research relied on convenience sampling to recruit participants who were primarily undergraduate psychology students and members of the online population who may not fully represent the population from which the sample has been drawn. The overrepresentation of young, female participants in the sample raises concerns about age and gender bias and warrants further investigation into potential age and gender-specific effects on AI interactions. Future research should conduct different sampling techniques and data collection to study a more diverse range of participants. However, it should be noted that other sound studies similarly include undergraduate students (Cheung and Vogel 2013; Shane-Simpson et al. 2018). Second, this study treated physical and mental health issues as separate entities; however, many health issues are a combination of physical and mental health symptoms. Future studies may wish to study a larger and more complex range of health issues. Third, our study was limited to an Australian sample. As Australia is a developed country with a universal healthcare system, participants may not need ChatGPT to treat their health issues. Based on our initial examination, future studies should recruit from various countries to understand the influence of income and healthcare systems on the willingness to use ChatGPT. Finally, our sample did not address the issue of urgency, which may also impact a user's decision to access online health advice. As such, future work should also measure health-related personal characteristics to measure the effect of health status (e.g., ill versus sick, chronic versus acute conditions) on behavioral intentions to use AI for health services.

6 Conclusion

This study drew upon existing literature to measure participants' behavioral intentions to use ChatGPT in two healthcare scenarios: physical and mental health. An eTAM was designed to examine variables that predicted participants' behavioral intentions to use ChatGPT for physical and mental health services. To the best of our knowledge, this is the first study to assess users' behavioral intentions to use ChatGPT for physical and mental healthcare. The findings emphasized the need to establish user trust and PU of ChatGPT in healthcare. For mental health LLMs, privacy concerns were a significant negative predictor, and it was suggested that companies and governments proactively address this concern through safeguards and additional regulatory action. For physical healthcare, companies may wish to increase users' PEOU by simplifying the user experience by providing clear instructions and methods of receiving user feedback. Additionally, this study found that the pattern of significant predictors and mean differences in eTAM constructs differed between scenarios, demonstrating that users' behavioral intentions cannot be generalized across uses of AI in physical and mental healthcare. This framework can be used by non-experts, designers, and AI stakeholders to build a comprehensive understanding of behavioral intentions when using ChatGPT for health services.

Appendix

See Table 5.

Table 5 Pearson correlation coefficients among study variables

1	2	3	4	5	6	7
Physical healthcare						
1. Behavioral Intention	−0.080	−0.070	0.585***	0.471***	0.577***	−0.229***
2. Age		−0.088	−0.048	−0.09	−0.143*	−0.033
3. Gender			−0.050	−0.018	−0.020	−0.041
4. PU				0.574***	0.597***	−0.251***
5. PEOU					0.457***	−0.130
6. Trust						−0.253***
7. Privacy concerns						
Mental healthcare						
1. Behavioral Intention	−0.030	−0.027	0.626***	0.443***	0.574***	−0.210**
2. Age		−0.088	−0.038	0.003	−0.127	0.012
3. Gender			−0.105	−0.051	0.002	0.059
4. PU				0.627***	0.664***	−0.075
5. PEOU					0.459***	−0.052
6. Trust						−0.200**
7. Privacy concerns						

*Correlation is significant at the 0.05 level (2-tailed).

**Correlation is significant at the 0.01 level (2-tailed).

***Correlation is significant at the < 0.001 level (2-tailed).

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Data availability Data is available upon request.

Declarations

Competing interest The authors declare no competing interests.

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