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Exploring Users' Acceptance and Engagement With Mental Health Chatbots: Insights From an Integrative Review

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ABSTRACT

Background: The potential of well-being chatbots as supportive tools in mental healthcare is increasingly recognised. Nevertheless, user acceptance remains low, highlighting the need to understand the factors influencing adoption and engagement.
Objective: The purpose of this study is to identify the factors influencing user acceptance and engagement with chatbots and to generate insights that can inform the design and implementation of more effective chatbot interventions for mental well-being.
Methods: Following the PRISMA 2020 guidelines, an integrative review was conducted in June 2024. Literature searches were carried out in Web of Science, Scopus, PubMed, IEEE Xplore and ScienceDirect to identify peer-reviewed articles published between January 2010 and May 2024. Thematic analysis was employed using an inductive approach.
Results: From a total of 1232 papers identified, 20 studies met the inclusion criteria. The findings developed three themes, which involve technological factor, user factor and environmental factor. Different subtopics within the technological aspects have different effects on user behaviour. Technological limitations and excessive anthropomorphism have emerged as key barriers to user–chatbot interaction; empathy, interactivity, user-centred design, ease of use, personalisation, usability and stability were found to promote user engagement. From the user perspective, barriers included lack of motivation, low trust, privacy concerns and effort expectations, while facilitators encompassed enjoyment, positive attitudes, learning opportunities and emotion. Environmental factors could influence user adoption behaviour, for instance, advertising and social influences.
Conclusions: Multiple interdisciplinary factors have been found to influence user engagement with chatbots for mental well-being. This will contribute to refining extant theories and fostering interdisciplinary collaboration. Moreover, this study provides a valuable source of instruction for designers and developers of health chatbots.

1. Introduction

The growing demand for mental health services and the shortage of medical resources are among the significant public health challenges affecting global human well-being. In some countries, up to 90% of people with mental health conditions do not have access to treatment [1]. Against this backdrop, chatbots have emerged as a promising digital intervention tool, with AI-driven chatbots in particular leveraging natural language processing and machine learning technologies to advance understanding and content response. Academic and business circles have shown keen interest in the role of intelligent dialogue systems in assisting mental health treatment, which is further driving the development of well-being chatbots. Well-being health chatbots provide a variety of services, including mental health education, emotional detection and assessment, mindfulness meditation training, social–emotional companionship and support and primary interventions using cognitive behavioural therapy. These services help to alleviate issues such as insufficient mental health service resources and low accessibility [2–5]. Chatbots generally achieve high satisfaction rates in mental health screening, diagnosis and treatment, particularly concerning mental health education and self-compliance [6]. A controlled experiment on the well-being chatbot showed that participants using Woebot experienced a significant reduction in depressive symptoms, as measured by the Patient Health Questionnaire-9, during the study period. Participants in the control group did not experience such a reduction [7]. A literature review on conversational agents in mental health indicated that all 13 included studies reported a decrease in psychological distress levels following the intervention [8]. However, some studies have found that chatbots may misinterpret information and provide misleading advice, which could harm users or have negative ethical implications [9, 10]. Users are concerned about privacy protection issues, specifically whether data collected during interactions with the well-being chatbot is properly protected; this has become a barrier to their continued use [11].

Young adults (typically aged 18–35) consistently emerge as the primary user group in most studies [12, 13]. Several studies highlight that females constitute more than 60% of users, and highly educated individuals are similarly overrepresented [14–18]. In terms of global adoption, chatbot use is growing in both developed and developing countries. Nevertheless, user numbers are predominantly concentrated in Europe, North America and select developed Asian nations, particularly for chatbots driven by artificial intelligence [19, 20]. A primary cause of these phenomena is the digital divide, manifested in the general public's insufficient digital literacy and barriers to technology access stemming from global socioeconomic and technological disparities.

To ensure the successful implementation and adoption of well-being chatbots in the field of mental healthcare, it is essential to understand the factors that influence user acceptance and interaction. Accordingly, this study conducts an integrative review of the existing literature to identify such factors and analyse them thematically. The findings of this research are expected to contribute to the extension of theoretical models concerning user behaviour in health information technology while also offering practical insights and recommendations for technology practitioners and policymakers involved in the development and deployment of well-being chatbots. To achieve the research objectives, the following research questions are proposed.

Question 1: What are the main factors that influence users' acceptance and engagement with chatbots?

Question 2: What are the insights of these factors that influence users' acceptance and engagement behaviour?

2. Methods

2.1. Database Search

This integrative review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [21]. A comprehensive search strategy was developed to identify relevant studies across five major electronic databases: Web of Science, Scopus, PubMed, IEEE Xplore and ScienceDirect. To ensure methodological rigour, the search terms were organised into three conceptual domains: (1) conversational agents, (2) mental health and (3) acceptance/adoption. Within each domain, a combination of controlled vocabulary terms and free-text keywords was employed. Boolean operators (AND/OR) were applied to refine and integrate the search concepts. The general search structure was as follows: (“chatbot” OR “conversational agent” OR “conversational system” OR “conversational bot” OR “CA”) AND (“wellbeing” OR “well-being” OR “mental health” OR “psychological health”) AND (“accept*” OR “use” OR “apply” OR “engage”). The search was conducted without restrictions on study design but was limited to peer-reviewed publications in English. Where available, database-specific filters (e.g. article type) were applied to enhance precision. The complete and tailored search strategies for each database are provided in Table 1.

2.2. Inclusion and Exclusion Criteria

This integrative review is aimed at exploring the factors influencing user acceptance and engagement with mental health chatbots. There are no restrictions on population groups, regions, specific mental health conditions, or study types, aiming to maximise the identification of factors influencing the adoption of mental health chatbots. Inclusion criteria include studies examining factors influencing users' adoption and interaction with mental health chatbots, with articles limited to English-language peer-reviewed journals published between

TABLE 1 | Search strategy.

Database	Filters in a search engine
Web of Science	Search within: Topic Article type: Article Language: English Publication date: From 2010/01/01 to 2024/05/31
SCOPUS	Search within: Article title, abstract and keywords Article type: Article Language: English Publication date: From 2010/01 to 2024/05
PubMed	Search within: Title/abstract Article type: Clinical trial, review and systematic review Language: English Publication date: From 2010/01/01 to 2024/05/31
ScienceDirect	Search within: Title, abstract and keywords Article type: Research articles Language: English Publication date: From 2010/01 to 2024/05
IEEE Xplore	Article type: Journals Publication date: From 2010/01/01 to 2024/05/31

January 2010 and May 2024. The year 2010 was chosen because chatbots aimed at mental health and well-being were first applied in practice that year [22]. During the screening process, studies not addressing factors influencing user adoption of mental health chatbots were excluded. This includes studies focusing solely on feasibility and effectiveness, technical descriptions and articles unable to address the research question (see Table 2).

2.3. Screening and Study Selection

All retrieved articles were imported into the reference management software Mendeley, where duplicate records were removed. The remaining studies underwent a multistage screening process. First, based on predefined inclusion and exclusion criteria, the first and second authors independently screened the article titles. In cases of disagreement, the abstracts were further assessed until consensus was reached. Second, both authors independently conducted a comprehensive evaluation of the abstracts of the selected articles. Any discrepancies were resolved through discussion after reviewing the full text. If consensus could not be reached, a third author was invited to participate in the discussion until agreement was achieved. In the third stage, the first author assessed the full texts of the selected articles, and the second author verified the assessment results to ensure consistency.

2.4. Data Analysis

An inductive thematic analysis was conducted to qualitatively examine factors influencing users' acceptance of well-being chatbots. This approach, independent of predefined theoretical frameworks, enabled an open exploration of behavioural determinants [23]. The analysis followed Braun and Clarke's [23] six phases: data familiarisation, coding, theme generation, theme review, theme definition and naming and report writing [23]. The first author generated initial codes from the full texts, which were reviewed by the second author. Themes were subsequently developed and refined through iterative discussions between the first and second authors. The third author then reviewed the results, and all three authors collaboratively finalised the themes and subthemes. Any discrepancies were resolved through discussion until consensus was reached. The finalised themes and subthemes are summarised in the thematic analysis section.

TABLE 2 | Eligibility criteria.

Category	Criteria
Inclusion	The study involved factors affecting user acceptance, use and engagement in mental health chatbots, as well as the current situation
	Articles were published in peer-reviewed journals from January 2010 to May 2024
	Articles are written in English
Exclusion	Feasibility and efficacy study
	Technical description
	Did not answer the research questions

2.5. Quality Assessment

Quality appraisal was conducted using the JBI Critical Appraisal Tools and was independently completed by the first and second authors [41]. The appraisal outcomes were then compared, and any discrepancies were resolved through discussion until consensus was reached. No studies were excluded on the basis of quality concerns. A total of 20 articles were appraised using the JBI checklist appropriate to their respective study designs, including cross-sectional studies ($n = 7$), mixed-method studies ($n = 3$), expert opinion ($n = 1$), qualitative studies ($n = 5$) and reviews ($n = 4$). For the three mixed-method studies, both qualitative and either quasiexperimental or cross-sectional appraisal tools were applied (see Supporting Information 1).

3. Results

The subsequent sections provide a systematic account of the findings from the integrative review, encompassing the search outcomes and an overview of the included studies, followed by a thematic analysis of the selected literature.

3.1. Search Outcomes and Overview

The database search yielded 1232 records in total. After removing 460 duplicates, 772 records remained for screening. Based on titles and abstracts, 630 records were excluded as they did not meet the eligibility criteria. The full texts of 142 articles were then assessed for eligibility. Of these, 122 were excluded for the following reasons: focus on feasibility or efficacy of chatbots ($n = 63$), technical descriptions ($n = 14$) or lack of relevance to the research questions ($n = 45$). Ultimately, 20 studies met the inclusion criteria and were included in the final synthesis. The characteristics of these articles are described in Table 3. They applied different types of research methods and were published between 2010 and 2024. The study selection process is detailed in the flow diagram (Figure 1).

3.2. Demographic Character

Of the 20 studies reviewed, 11 reported the mean age of participants. Among these, 45% had a mean participant age below 25 years, while none reported a mean age exceeding 45. Research on well-being chatbots has predominantly involved young adults, particularly university students. Female participants generally outnumbered males across the studies. Geographically, the research was concentrated in regions with relatively advanced AI development, including Europe, the United States, China, the United Kingdom and other parts of Asia. However, these studies did not provide an in-depth exploration of content tailored to diverse cultural backgrounds. Only one study noted a participant suggestion to incorporate

TABLE 3 | Overview of selected articles.

No.	Reference	Objective	Method/sample	Main findings
1	L. Li et al., 2024 [40]	Adoption and continued use	Cross-sectional study, $N = 393$	1. For nonusers, performance expectancy, price values, descriptive norm and psychological distress positively impact intention; AI hesitancy and effort expectancy negatively impact adoption. 2. For users, performance expectancy, price value, descriptive norm and injunctive norm have a positive influence on continuing to use.
2	Prakash and Das [34]	To explore factors influencing the use of AI chatbots in mental healthcare by examining user perceptions	Qualitative study, $N = 1826$	Four themes and 12 subthemes were developed, which presented the factors influencing users' adoption behaviour decisions.
3	Szinay et al. [42]	Explore experience and reasons for usage, and do not use in a range	Qualitative study, $N = 17$	1. The factors that influence the ability of users are the application's functions related to guidance, managing health information, monitoring and reducing cognitive loading. 2. The factors that enhance adoption are tailoring and support from peers and professionals. 3. Replies, rewarding, encouraging, targeting, making plans, confidence and promising drive users' engagement with the well-being application.
4	Khosravi and Azar [43]	Review the factors influencing users' engagement with chatbots	Systematic review, $N = 1494$	Chatbot design and outcomes, as well as the perception and characteristics of users, are the major themes related to users' engagement.
5	Salamanca-Sanabria et al. [24]	To explore the perceptions of mental health supporters, particularly CA, for intervening in mental disorders	Qualitative research, $N = 30$ (university students) and 11 (mental health supporters)	Shame, personalisation and perceptions of mobile interventions were the main influences.
6	Moilanen et al. [28]	Exploring users' usage and perceived trust in a CA	Mixed method, $N = 80$	Trust is influenced by personal experience, perceived reliability and outcomes.

(Continues)

TABLE 3 | **(CONTINUED)**

No.	Reference	Objective	Method/sample	Main findings
7	Kettle and Lee [4]	To explore users' experiences of chatbots and identify key engagement factors	Mixed method, $N = 60425$ (posts) and 19 (participants)	The experience of interacting with a dialogue agent and how they communicate can influence engagement and the perceived role of CA.
8	Martinengo et al. [35]	To evaluate nine CAs for users with depression or suicidal tendency	Cross-sectional study, $N = 9$	Anonymous, empathy and nonjudgmental interactions with users were the same as those in psychotherapy in person.
9	Abd-Alrazaq et al. [25]	Exploring patients' perceptions and experiences of mental health chatbots	Scoping review, $N = 1072$	Ten themes were developed from findings.
10	Boucher et al. [30]	Explore users' perceptions of AI chatbots in the field of mental health, the impact of individual differences and privacy and ethical considerations	Expert opinion	Users have positive attitudes toward chatbots, and individual and situational factors influence user engagement and experience.
11	Koulouri et al. [38]	To explore the acceptability of chatbots for young adults' mental healthcare	Cross-sectional study, $N = 150$	Chatbots can be acceptable, but there are challenges regarding technology and the environment. User-centred development and rigorous assessment of the system should be conducted.
12	Maharjan et al. [31]	Analysis of the actions taken by the interviewees about the limitations of CA and the forms in which CA is evaluated in their social circles	Qualitative study, $N = 20$	Participants' actions for CA's shortages, personalisation of CA and values of user and social relationship on CAs are emphasised, as well as some limitations about CA's design.
13	Xue et al. [32]	Comprehensively evaluate chatbots to identify shortcomings and improve future designs	Scoping review, $N = 36$	The differences in chatbots' conversational abilities are particularly pronounced in terms of empathy, sense of humour and personalisation.
14	Gbollie et al. [39]	Exploring the attitudes of university students from SA universities for intentions to use a digital mental health solution	Cross-sectional study, $N = 17,838$	University students show positive attitudes toward digital solutions for mental health.

(Continues)

TABLE 3 | (CONTINUED)

No.	Reference	Objective	Method/sample	Main findings
15	Zhu et al.Whang [36]	To provide a framework for users' satisfaction and continuance intention on the mental health chatbot	Cross-sectional study, $N = 371$	Personalisation, fun, learning and conditions under COVID-19 positively impact users' satisfaction and continuance intention.
16	Denecke et al. [33]	Introducing SERMO and evaluating the user experience	Cross-sectional study, $N = 21$	SERMO performs well on efficiency, clarity and appeal.
17	Park and Kim [29]	Exploring factors influencing the use of chatbots' digital content based on the technology acceptance model and satisfaction theory	Cross-sectional study, $N = 278$	The levels of depression, perceived usefulness and prosocial interaction experienced by participants were found to be significant positive factors influencing people's intention to use MyMentalPocket.
18	Zhu et al. Jansen. [37]	Based on the consumer value theory, a framework is proposed to explore the key factors that affect users' experience and satisfaction with chatbots.	Mixed method, $N = 295$	Personalisation, enjoyment, learning and situation positively influence user experience and satisfaction.
19	Chaudhry and Debi [26]	Exploring user engagement and technology awareness with Wysa (AI chatbot).	Qualitative study, $N = 159$	Seven themes were developed, which illustrate the strengths and limitations of AI chatbots.
20	Abd-alrazaq et al. [27]	Outline the characteristics of chatbots for mental health reported in empirical literature.	Scoping review, $N = 53$	Chatbots feature virtual avatars. The robots steer conversations, with text-based input accounting for nearly 50% of interactions. Research in the field of mental health remains in its infancy.

Abbreviation: CA, conversational agent.

region-specific terminology into health applications to enhance relevance and engagement—a design consideration supported by Jack et al. [44]. The use of localised language features, such as colloquial expressions, has been shown to improve perceived relevance and interaction involvement during user–chatbot dialogue [24]. Additionally, the proportion of participants with higher education qualifications was substantially greater than that of those without across the 10 studies reporting educational background. These results indicate that well-educated young adults demonstrate relatively higher interest in using well-being chatbots compared to other demographic groups. Meanwhile, this highlights a gap in published research concerning elderly populations and individuals with lower educational attainment. The digital divide's impact on technological accessibility exacerbates inequalities among different age groups, income brackets and educational levels within society. All demographic information is shown in Table 4.

3.3. Thematic Analysis

A thematic analysis was conducted on the data from the included studies, yielding three main themes: technological factors, user factors and environmental factors. Technological factors pertain to the technical characteristics of chatbots, such as acceptability, effectiveness, ease of use and empathy. Given that chatbot technology is still in an early stage, technical limitations can pose barriers to user experience and interaction, highlighting the importance of user-centred design. User factors mainly encompass users' perceptions, emotions, confidence and motivation, which directly influence their willingness to adopt and engage with the chatbots. Environmental factors involve social influences and interdisciplinary contextual elements, such as advertising, that can affect user behaviour. Each theme is further divided into several subthemes, summarising the key findings from the included literature regarding users' adoption and engagement with well-being chatbots (see Tables 5, 6 and 7).

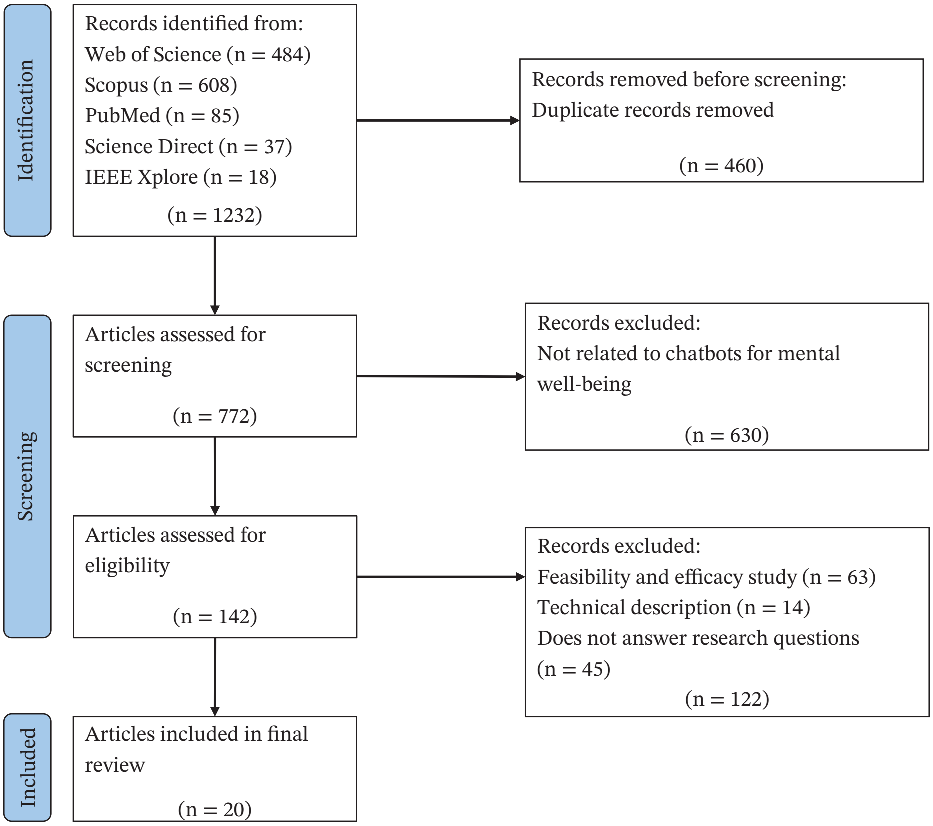

FIGURE 1 | PRISMA flowchart describing the study identification and selection.

4. Discussion

4.1. Technical Limitations and Effectiveness

The development of AI chatbots is still in its infancy, and scholars have reached different conclusions about their effectiveness. Several scholars have concluded that their chatbots are effective for specific users after development and measurement and have received positive feedback from users [45–47]. Evidence suggests that chatbots can alleviate depression, stress and negative emotions [48]. However, it has also been suggested that none of the respondents who used mental health apps found the technology useful [38]. Contradictory findings exist across different studies, with the validation of chatbot effectiveness being linked to technical limitations and individual variations. Chatbots can assist users in cultivating self-care and health literacy, but they cannot replace professional psychological therapy [49]. Limited empathy and an inability to establish therapeutic relationships constrain the efficacy of chatbots [50]. When users exhibit suicidal or self-harm tendencies, certain chatbots fail to intervene promptly during sudden crises, posing significant safety concerns for well-being chatbots [24].

4.2. Anthropomorphism

Anthropomorphism represents a fundamental characteristic of chatbots. Some studies have shown that users are satisfied with robot anthropomorphism, but others have shown that inappropriate anthropomorphic visuals can negatively affect participants' self-disclosure and companionship [51]. When machine-based assistants present anthropomorphic qualities, users avoid seeking their help in achievement environments [52]. For this reason, being self-reliant is praiseworthy, whereas dependence is a sign of low self-esteem [53]. Users search for answers on their own before verifying the answer with the robot assistant or seeking help if the search fails [52]. Some scholars have argued that if a chatbot becomes too human, it can significantly reduce users' trust in it [54, 55]. An overly sociable and user-recognisable chatbot can cause users to have concerns about their privacy, which is related to the user's personality; therefore, developers tend to design chatbots to be neutral to have an optimal impact on mental health [28]. Research on the phenomenon of chatbot anthropomorphism remains in its infancy; further exploration is required in the future.

4.3. Interactivity and Responsiveness

The interactive capability and responsiveness of well-being chatbots are pivotal determinants of user experience. However, user perceptions of chatbot conversational styles are divergent. For instance, a humorous and dynamic personality may be suitable for users seeking casual conversation, fostering a sense of relaxation and positive affect. Conversely, for a user experiencing emotional distress, such a style may be perceived as incongruous and inappropriate. The user experience derived from different interaction styles is closely intertwined with individual preferences, the user's immediate emotional state and needs and

TABLE 4 | Demographic information.

Demographic	*n*
Mean age (years)	
18–25	5
26–35	2
36–45	4
Above 45	0
Not reported or not applicable	9
Female gender rate	
$< 50\%$	5
$\geq 50\%$ and $< 70\%$	7
$\geq 70\%$	2
Not reported or not applicable	6
Country	
United States	1
United Kingdom	2
Singapore	1
Denmark	1
Australia	1
China	2
Switzerland and Germany	1
South Korea	1
Global population	10
College or above degree rate	
$< 30\%$	0
$\geq 30\%$ and $< 50\%$	1
$\geq 50\%$ and $< 70\%$	3
$\geq 70\%$	6
Not reported or not applicable	10
Clinical profile/eligibility	
Depression and anxiety	2
Affective disorders	1
University student	3
Young adults aged from 18 to 24 years	1
Interested in a well-being application or considering changing behaviour through using the application	2
Users' reviews of the well-being application	1
Not reported or not applicable	10

cultural background, presenting a significant challenge to the design of chatbot interactivity [4]. Involving users in the design process to gain a comprehensive understanding of their needs and interactive perceptions across diverse contexts is crucial for enhancing chatbot interactivity. Responsiveness constitutes another critical metric for user experience. Users generally expect timely replies and an appropriate pace of dialogue from chatbots. Effective responsiveness in mental health chatbots can foster user trust and potentially reduce feelings of frustration. While interactivity and responsiveness share the convergent goal of meeting user needs, they often present a trade-off in terms of technical implementation and resource allocation. High-level interactivity, necessitating sophisticated technologies such as affective computing and natural language processing, inherently requires greater processing time. This computational demand can consequently compromise response speed. Therefore, achieving an optimal balance between interactivity and responsiveness to ensure a superior user experience represents a forthcoming key objective for designers and developers of well-being chatbots.

4.4. Accessibility and Acceptability

Research shows that although young adults are generally enthusiastic about emerging technologies, they tend to adopt a "wait-and-see" attitude. Their usage intentions are not fixed but malleable, significantly influenced by technological iterations and social recognition. With improvements in key areas such as accessibility, usability and personalisation of chatbots, their willingness to use them has increased [38]. In contrast, promoting acceptance among the elderly faces challenges. This group often faces issues such as unfamiliarity with mobile applications, lack of previous experience and the need for more learning effort and cognitive requirements compared to younger users. Another study illustrated that young people and the elderly exhibited similar assessments regarding acceptability, and no significant differences had been identified [45]. All these make the design and deployment of well-being chatbots in health interventions complex. It highlights the conflict between the pursuit of technological advancement and the principle of universal applicability. Overemphasising technical complexity and advanced features that enhance interactive experiences may instead exacerbate the digital divide. A special situation occurred during the COVID-19 pandemic. In this crisis situation, the download and use of health chatbots soared [56]. This indicates that external environmental factors can overcome the inherent barriers in the short term, with an interaction existing between individuals' propensity to adopt technology and societal environmental demands. The accessibility and acceptability of technology are not always positively correlated; in specific circumstances, a negative correlation emerges.

Overall, the acceptance and continuous use of health chatbots are not determined by a single factor but by a complex connection among personal characteristics, technical attributes and the external environment. The relationships among these factors are often dynamic and sometimes contradictory. Therefore, it is of great value to study the theoretical basis of the intention to use. Understanding complex situations is crucial for promoting the acceptance of chatbots as supplementary healthcare tools, ensuring that they can reach a wider range of beneficiaries in need.

TABLE 5 | Technological factor.

Theme	Subtheme	Explanation and reference
Technological factor	Technical limitations	- Personalised features for handling special events. For example, dealing with suicidal thoughts [24] - Mechanical language, content is too superficial and lack of comprehensibility [25] - The limitations of AI will affect the user experience [26] - 92.5% of chatbots rely solely on decision trees to generate responses, whilst only 7.5% utilise machine learning techniques [27]
	Humanisation	- The human element of AI is welcome [26] - Overly human, recognisable, understandable to the user and can also make users feel distrustful and concerned about privacy [28]
	Easy to use	Users can use the application without too much effort ([25]; [29])
	Accessibility	- Easy to connect and access connected applications at any time [30] - Real-time support is available anytime, anywhere [26]
	Empathy	Ability to empathise with users' emotions and provide personalised health advice [31]
	Interactivity and responsiveness	- Friendly and emotional communication [25] - Replies were repetitive, slow or too factual [25] - The control interface and appearance are not attractive enough [26] - Gamification, rewarding, reminder and plot design [24]; - Replies to suicidal thoughts [32]
	Effectiveness	- Provide emotional support and build a trusting relationship with the user [30] - Provides clear and accurate feedback [33]
	Suitable anthropomorphic	- Respect users [30] - Being attractive [33]
	Transparency	Understanding more information about the chatbot, including rules, limitations and expression style [28]
	Usefulness and performance expectancy	- Conversations and learning in a private environment make users feel good; check-ins increase responsibility, improve self-efficacy and self-confidence; evoke user memories [25, 26, 29] - The ubiquity and convenience of AI chatbots are impossible to achieve in human therapy [34]
	Content and appearance	- Users are satisfied with videos, games and topics [25] - Videos that are too long or lack relevance affect the user experience [25]
	Personalisation	- Personalisation characteristics and setting [35, 36] - Personalised design in terms of dialogue content, user interface, delivery channels and functionality [32, 37]
	User-centred	- A user-centred approach should be adopted and evaluated in the development of chatbots [38] - Good privacy and little criticism facilitate user self-disclosure [30]
	Price value	Chatbots offer unparalleled price advantages [34]

TABLE 6 | User factor.

Theme	Subtheme	Explanation and reference
User factor	Motivation	A desire for consistent and predictable interactions [26]
	Trust	- Users express a high degree of trust in anonymity, confidentiality and objectivity [25] - An environment of trust promotes well-being [26] - Trust in the technology and trust in the technology provider will influence users' behaviour with chatbots [34]
	Privacy concern	- Concerns about sensitive personal information can affect individual self-disclosure [35] - The lack of privacy protection makes users reluctant to use AI chatbots [34]
	Stigma	Users feel shame about mentioning personal privacy, especially mental health issues [39]
	Perceived risk and benefit	Users perceive that the potential risks and benefits associated with using AI chatbots may affect their willingness to use them [34]
	Effort expectation	Users are less likely to use it when it is technically difficult, especially for older adults [34, 40]
	Enjoyment	User experiences on hedonic quality were assessed at high and neutral levels [25, 33, 36, 37]
	Emotion	Emotional self-disclosure helps users engage meaningfully with chatbots [32]
	Learning	Users can enrich their knowledge [36, 37]

TABLE 7 | Environmental factor.

Themes	Subtheme	Explanation and reference
Environmental factors	Advertising	Corporate advertising or sponsorship of healthcare institutions will reduce the user's trust and will not be used [28]
	Social factor	If doctors, friends or community interest groups recommend some smartphone apps, users will consider trying them out [34, 40]

4.5. Privacy Concerns and Ethics Issues

The majority of users lack sufficient awareness regarding the protection of their health data, with a subset of users exhibiting a lack of concern for this issue, a phenomenon that is particularly prevalent among younger demographics [57]. Only a minority of users are concerned about how their health data is handled, whether chatbot providers will use it to generate revenue and whether they will be rewarded as a result [58]. Privacy concerns are importantly related to individual differences [46]. Indeed, the protection of customer data is of paramount importance at every point in the entire chatbot product cycle. The management of substantial personal data—including storage, access, future utilisation, legal compliance and response to breaches—is a crucial consideration that must be addressed by the relevant stakeholders.

In the field of data governance, states and relevant organisations have successively enacted legislation to protect individual privacy and regulate the management of customer data by AI product providers [59]. It is incumbent upon providers to ensure that users are fully informed of how their data will be handled before the placement of their products on the market [28]. This information must be made clear in the form of laws and regulations, and it must include details of how data on health will be obtained, how it will be used, how it will be stored, who will have secondary access to it and how it will be distributed should it generate revenue [60, 61]. The protection of personal privacy is a matter of concern for users and the future development of AI chatbots. Developers and users should prioritise personal privacy alongside considerations of product design and utilisation. While the government has promulgated regulations to address these issues, significant progress is still required for their effective implementation.

Chatbot technology in mental health is still in its infancy. Chatbots are unable to engage in rational and ethical therapeutic dialogue with patients and build therapeutic relationships with users in the same way that humans do [62]. It is recommended that chatbots be used as an adjunctive therapeutic tool and should not be a completely separate therapeutic subject [63]. Bias should be avoided in algorithms and interaction interfaces during the design and development of chatbots [63]. Harm to users can be reduced by completing bias testing before the chatbot enters service because bias in software can have a wider range of adverse effects than bias in reality [64]. Software fairness should be part of the responsibility of designers and developers.

4.6. Theoretical and Practical Implications

Factors influencing user engagement with chatbots come mainly from the user and the technology, as well as other social and environmental factors. Some factors overlap with major IS theories, for instance, UTAUT, the technology acceptance model, the theory of planned behaviour and game theory. Some factors are not included in the existing theories, such as advertising, overhumanisation, visual interface, content and presentation. They will refine the existing theoretical models to explore user behaviour from different perspectives. Another important contribution is the construction of interdisciplinary models. Different fields like marketing, psychology and human–computer interaction will be merged with information systems to explore human engagement behaviours with chatbots and future interactions. Interdisciplinary theoretical integration will become a new trend in behavioural theory research.

The findings of this study offer valuable insights for designers and developers of well-being chatbots, with the potential to enhance the service quality of digital interventions in public health and well-being. The results indicate that factors across technological, user and environmental dimensions are likely to improve user adoption intention and overall experience. From a technological perspective, it is essential to refine the knowledge base and enhance the training of natural language understanding models [65]. This involves continuous supervised learning and iterative improvement of models and dialogue strategies using high-quality data. System functionality and effectiveness should be consistently monitored, with user feedback serving as a critical input for optimisation [66]. A balance between a chatbot's responsiveness and interactivity must be maintained. Technical analysis of response latency should be conducted, and in cases of delay, users should be reassured through linguistically appropriate interactive strategies. Furthermore, interaction quality can be significantly improved by incorporating an understanding of users' linguistic habits, cultural backgrounds and real-time emotional states. From a user perspective, high-quality interactions and appropriately paced responses contribute to building user trust. Enhancing affective computing and emotion detection capabilities allows for accurate recognition of users' current emotions [67]. Particularly in cases of extreme negative affect, such as suicidal ideation, emergency response protocols must be activated. Chatbot functions should be tailored to users' age, personality, preferences, cultural context and skill levels to meet personalised needs across all age groups. A user-centred approach should be adopted throughout the entire chatbot lifecycle—design, development and postdeployment—by actively involving users to understand their diverse needs, including enjoyment, learning and emotional support [68]. This ensures maximum usability and usefulness. Prior to use, data protection policies should be clearly communicated to raise user awareness of privacy issues, in compliance with relevant regulations and in the interest of safeguarding user rights. From an environmental and social perspective, chatbot companies should monitor public perception and social feedback, particularly evaluations on social media platforms, as these influence user trust and adoption. Appropriate advertising and science-based promotional efforts may help increase awareness and willingness to use among broader population groups. By addressing these interconnected aspects, well-being chatbots can achieve higher user acceptance, foster sustained engagement and ultimately deliver more effective and responsible digital well-being services.

4.7. Limitations and Future Research

This study outlines key factors influencing the acceptance and adoption rates of well-being chatbots while analysing demographic and socioeconomic information. However, we observed a significant gap in research concerning mental health chatbots for elderly individuals and those lacking digital literacy, resulting in insufficient findings regarding acceptance and interaction factors for these specific groups. Research targeting older adults, individuals with lower educational attainment and those with insufficient digital literacy will constitute a crucial direction for future studies. Concurrently, we appeal to the academic community and relevant enterprises to place greater emphasis on the needs of elderly individuals and specific groups in future endeavours, particularly concerning the accessibility and ease of use of chatbots. We advocate for the active involvement of older adults and other specialised groups throughout the entire product lifecycle during the design and development process. This approach will contribute to advancing equity in digital healthcare services and ameliorating the global digital divide. Another limitation is that the study does not develop a conceptual model tailored to the use of chatbots in the mental health domain, drawing upon relevant theoretical frameworks. Future research should therefore explore these aspects in greater depth, with particular attention to cross-demographic and cross-cultural differences, as well as the theoretical advancement of conceptual models to guide system design and application in mental well-being contexts.

5. Conclusion

This study examined the factors influencing users' acceptance and engagement of well-being chatbots and identified three overarching themes: technological factor, user factor and environmental factor. The findings highlight that the main barriers to adopting innovative technologies lie in technical limitations and the digital divide. In parallel with advancing responsible technological development and improving the quality of data used to train artificial intelligence systems, the study underscores the importance of adopting user-centric design principles. Furthermore, it emphasises the critical role of privacy management and ethical governance in ensuring the trustworthy integration of well-being chatbots. These findings will contribute to the advancement and extension of existing theoretical models. From a practical perspective, they highlight the importance of fostering responsible development of chatbot technologies and ensuring the quality of data used in artificial intelligence applications. Moreover, they underscore the need to promote user-centred design while giving due attention to privacy protection and ethical governance.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Supporting Information 1. Quality assessment.

Supporting Information 2. PRISMA 2020 checklist.