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Understanding the Intention to Use Mental Health Chatbots Among LGBTQIA+ Individuals: Testing and Extending the UTAUT

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Abstract. This empirical study aims to test and extend the unified theory of acceptance and use of technology (UTAUT) in the context of mental health chatbot usage among LGBTQIA+ individuals. The proposed model uses UTAUT variables (performance expectancy, effort expectancy and social influence) as well as chatbot-related variables (willingness to self-disclose, perceived loss of privacy, and trust) to predict the intention to use a mental health chatbot. The online survey (N = 305) indicates that performance expectancy, social influence, and willingness to self-disclose positively predict chatbot usage intention, whereas effort expectancy negatively influences this intention. Moreover, previous experience with healthcare chatbots moderated the relationship between social influence and intention, age moderated the relationship between willingness to self-disclose and intention, and gender identity moderated the relationship between perceived loss of privacy and intention. Overall, the extended UTAUT proved to be useful in explaining technology acceptance of mental health chatbots among the LGBTQIA+ community.

Keywords: Technology acceptance; mental health chatbots; UTAUT; LGBTQIA+ community

1 Introduction

Mental health chatbots —empathic agents using natural language processing (NLP) to detect and reframe cognitive patterns of users [23]— offer great potential for individuals who suffer from mental health issues but lack access to treatments or are ashamed of their problems [1]. This is because chatbots are always available, easily accessible, cost-effective, offer a non-judgmental space and show both infinite patience as well as immediate feedback [15]. First studies testing applications such as Wysa [64] or Woebot [63] show promising results regarding the effectiveness of mental health chatbots in reducing feelings of stress [38], anxiety [21] and depression [20].

A widely used model to predict people's intention to use technology is the unified theory of acceptance and use of technology (UTAUT) [60, 61]. This model combines several variables derived from the technology acceptance model [17] and the theory of planned behavior [2] and has been used and adopted in numerous contexts [11, 45, 56, 62, 66]. There are at least two current-day trends that the UTAUT needs to be adapted to. First, the traditional UTAUT cannot fully explain the intention to use mental health chatbots as it neglects crucial chatbot-specific aspects like privacy, trust, and individuals' willingness to self-disclose to a chatbot. Second, research explaining technology acceptance has traditionally included gender as a dichotomous variable, whereas we now live in a society where boundaries are increasingly blurred between male, female, non-binary, transgender, and genderfluid identities [8, 9, 12, 13]. Thus, models should take these differential gender categories into account.

The LGBTQIA+ (Lesbian, Gay, Bi, Trans, Queer or Questioning, Intersex, Asexual and other sexual orientations (+)) community could particularly benefit from mental health chatbots. Research has repeatedly shown that this group runs a higher risk of developing a mental illness compared to heterosexual individuals [18, 50, 54, 65] since they still face bullying, harassment and violence [50]. At the same time, LGBTQIA+ individuals often lack the necessary social support and psychological assistance to understand their feelings and inclinations or are ashamed to seek help themselves [50]. Consequently, LGBTQIA+ users distinguish themselves in terms of technology use, because they have a heightened need for a safe, non-judgemental (online) space. Especially when they do not receive enough support from their family or friends, they more often use technologies and online platforms to search for like-minded individuals and other types of support. Also, they generally have a stronger urge for anonymity and therefore potentially a higher willingness to disclose to a chatbot [41]. Hence, this paper aims to answer the overarching research question to what extent the (extended) UTAUT can predict the behavioral intention to use a mental health chatbot among LGBTQIA+ individuals. To be able to test our hypotheses, as well as to answer the more explorative research questions, we chose a survey design. In doing so this study will provide a new perspective on the inclusion of chatbot-specific variables and gender identities into traditional communication models such as the UTAUT.

2 Theoretical Background

2.1 The UTAUT

The UTAUT was initially proposed by Venkatesh and colleagues [60]. In developing this model, the authors combined concepts from eight user acceptance models, among others the technology acceptance model [14, 17], the theory of reasoned action [19] and the innovation diffusion theory [49]. This way, Venkatesh et al. [60] created a unified and theory-based model that predicts user acceptance. According to the original UTAUT, three core variables predict the behavioral intention (BI) to use a certain technology: Performance Expectancy (PE; i.e., how useful one thinks the technology will be), Effort Expectancy (EE; i.e., how easy one expects the technology to be) and Social Influence (SI; whether one believes that one's social environment thinks one should use the technology). Moreover, in the UTAUT, these three relationships are moderated by age, previous experience with the technology (not for PE), gender [59] and voluntariness of use [60]. In the current study, the updated variable for gender is included in the extended model, and voluntariness of use is omitted because in the current study it is a constant (i.e., our research focuses on the voluntary usage of mental health chatbots [7]). Thus, the UTAUT hypotheses are:

H1: PE positively influences BI to use a mental health chatbot among the LGBTQIA+ community and this relationship is moderated by (a) age.

H2: EE positively influences BI to use a mental health chatbot among the LGBTQIA+ community and this relationship is moderated by (a) age and (b) previous experience.

H3: SI positively influences BI to use a mental health chatbot among the LGBTQIA+ community and this relationship is moderated by (a) age and (b) previous experience.

2.2 Extending the Model: Willingness to Self-Disclose, Perceived Loss of Privacy, Trust and Gender Identity

Willingness to Self-Disclose. We define WSD as the willingness of LGBTQIA+ individuals to entrust personal information to a mental health chatbot [15]. It has been suggested that mental health chatbots can be highly beneficial for self-disclosure because they provide an anonymous space without stigmatizing the user [3]. This is in line with studies that indicate high WSD to an empathic chatbot [10, 25, 32, 58]. Lucas and colleagues found that participants showed less fear of self-disclosure, more intense expressions of emotions, and overall, a higher WSD with a computer system as opposed to a human operator [37]. On the other hand, the lack of human empathy might decrease people's willingness to disclose personal information [15]. In any case, it is logical to assume that the higher the WSD, the higher the intention to use a mental health chatbot.

Moderations. We expect the effect of WSD on Behavioral Intention (BI) to be stronger for younger compared to older LGBTQIA+ individuals because younger people are often more familiar with modern technology and therefore more likely to entrust personal information to a mental health chatbot [51]. To our knowledge, previous research did not yet explore the moderating role of previous experience and gender identity in the relation between WSD and BI. Therefore, the present study answers the following research questions and tests one hypothesis.

H4: WSD positively influences BI to use a mental health chatbot among the LGBTQIA+ community.

H4a: The relationship between WSD and BI is moderated by age, such that the effect is stronger for younger LGBTQIA+ individuals than for older LGBTQIA+ individuals.

RQ1: To what extent does previous experience with chatbots moderate the relationship between WSD and BI?

RQ2: To what extent does gender identity moderate the relationship between WSD and BI?

Perceived Loss of Privacy. Perceived loss of privacy (LOP) is defined as the extent to which individuals think smart healthcare services such as mental health chatbots violate their privacy [36, 57]. In mobile health applications, where people disclose sensitive data, privacy is an important aspect to consider. One study did not find LOP to be a significant direct predictor of BI [36]. However, other studies did find a negative, direct effect of LOP on the acceptance of chatbot applications [35, 44].

Moderations. An explanation of these mixed findings can be found in people's level of experience with technology. Privacy concerns decrease with more Internet experience [5] which is in line with the findings of Bergström, who found that with most Internet situations, experienced people were less concerned [6]. Regarding the moderating effect of age, previous research has been inconclusive. Some studies found no differences due to research measurements [26, 55] or only small significant differences with younger people being more concerned about privacy [6]. Guo and colleagues found that the effect of privacy concerns on BI is stronger for younger users, whereas older users were not affected [24]. In contrast, Shehaan proposed different user typologies, with older consumers being more alarmed in contrast to younger users [53]. Accordingly, we test the following hypotheses and aim to answer the following research questions:

H5: LOP negatively influences BI.

H5a: The relationship between LOP and BI is moderated by experience, such that the effect is stronger for less experienced (compared to more experienced) LGBTQIA+ individuals.

RQ3: To what extent does age moderate the relationship between LOP and BI?

RQ4: To what extent does gender identity moderate the relationship between LOP and BI?

Trust. Trust in a chatbot is defined as the degree to which LGBTQIA+ individuals perceive mental health chatbots as dependable, reliable, and trustworthy in improving one's mental health [36]. Trust is a crucial factor for establishing strong bonds with someone and has shown to be equally important when it comes to human-computer interactions [15, 34]. Several studies indicate that trust is an antecedent for BI [36, 48].

Moderations. Schroeder and Schroeder investigated factors that influence trust in chatbots and found that individuals who are more experienced with chatbots and who are younger are more likely to trust a chatbot [51]. Simultaneously, transgender individuals often seek social support online [41]. Considering this unmet need and high online presence, transgender individuals may perceive mental health chatbots more positively, which in turn might increase their trust to use such a chatbot. To our knowledge, no study has yet examined how gender identity moderates the relation between trust and BI. Therefore, we expect and propose the following:

H6: Trust positively influences BI.

H6a: The relationship between Trust and BI is moderated by age, such that the effect is stronger for younger (compared to older) LGBTQIA+ individuals.

H6b: The relationship between Trust and BI is moderated by experience, such that the effect is stronger for more experienced (compared to less experienced) LGBTQIA+ individuals.

RQ5: To what extent does gender identity moderate the relationship between trust and BI?

The proposed extension of the UTAUT to the context of mental health chatbot acceptance among the LGBTQIA+ community is depicted in Figure 1.

3 Method

3.1 Sampling

Ethical approval was granted by the university's Ethics Review Board (project ID: 2021-PC-14159). The questionnaire was created in English to reach LGBTQIA+ individuals of different nationalities. We used purposive convenience sampling by sharing the survey on the first author's social media as well as posting a recruitment text in relevant LGBTQ+ Facebook groups and Reddit threads. Also, flyers with the survey QR code were spread at a Dutch university. Eligible participants were individuals older than 16 years who (potentially) identify as LGBTQIA+. Participation was completely voluntary and anonymous. Respondents were not compensated. Because of the length of the questionnaire (~ 10 minutes), the dropout rate was quite high (32,18%). In total, 354 valid responses were gathered. However, four respondents did not give consent, sixteen participants did not consider themselves as part of the LGBTQIA+ community, and four respondents were aged below 16. These respondents, together with those who did not pass the attention check (n = 28), were excluded from the data set. Additionally, we omitted one case whose answers indicated zero variance (straight liner). This leaves a final sample of N = 305 participants.

3.2 Pretest

The questionnaire was pre-tested with eight LGBTQIA+ individuals. Pre-testers indicated difficulties with imagining what a mental health chatbot would look like. We therefore included a screen recording of an existing mental health chatbot application (Wysa). In the 1 min 42 sec video, respondents saw an interaction with Wysa, during which the chatbot explains the importance of mental resilience and sends motivational GIFs (graphics interchange format – a series of pictures that can be static or dynamic [22]) and empathetic messages. Furthermore, participants saw which answer options are provided for the user (pre-selected or typing freely) and how a conversation with a mental health chatbot works in general.

3.3 Procedure

Data were collected between 9th-17th December 2021. Participants who clicked on the survey link or scanned the QR code were exposed to the information letter in the survey tool Qualtrics. Afterwards, participants gave informed consent. If participants did not give consent, they were automatically led to the end of the survey. All participants who agreed to the research terms were asked whether they consider themselves part of the LGBTQIA+ community. This question served to the exclusion of heterosexual and cisgender individuals. Next, respondents indicated their gender identity, age, level of education, mental health, and previous experience with chatbots. Respondents saw a short description and examples of chatbots, and were asked how often they have used these different types of chatbots in the past. Subsequently, we described the concept of a mental health chatbot and showed the video. After that, participants were exposed to the items concerning PE, EE, SI, BI, LOP, trust and WSD.

3.4 Measurements

Appendix 1 provides an overview of the original items and adjusted items. PE, EE, SI and BI were adapted from Venkatesh and colleagues' validated and widely tested scales [60]. Participants' WSD to a chatbot was adapted from Croes and Antheunis [15]. The scales for perceived LOP and trust were adapted from Liu and Tao [36]. All latent constructs were measured on a 7-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). Appendix 2 shows (very) high Cronbach's α values as well as *M* and *SD* of the main variables.

Age was measured with an open text entry and recoded into three groups (1 *SD* below average, average, and 1 *SD* above average).

Previous experience with chatbots was measured with the question: "How often have you used one of these chatbots in the past?" For customer service chatbots, healthcare chatbots, social messaging chatbots and other chatbots, respondents indicated their previous experience on a 5-point Likert scale ranging from "Never" to "A lot of times (>20 times)"

Gender identity was measured with the question: "Which of the following most likely describes you?" Participants could choose between "Female", "Male", "Non-binary", "Transgender", "Intersex", "Queer or Questioning", "I prefer not to say" and a text field for individual specification.

Level of education was measured with the question "What is the highest degree or level of education you have completed?", ranging from "No schooling completed" to "Doctoral or equivalent level".

Respondents also had to indicate whether they coped with mental health issues and, if so, whether they received professional help. Lastly, one attention check item ("Please click on 'Agree'") was included between the items addressing BI to check whether respondents paid attention throughout the questionnaire.

3.5 Analysis

Data analyses were carried out in SPSS. To describe the sample, a frequency analysis was conducted. By creating a scatterplot and histogram of the residuals, the assumptions of linearity and homoscedasticity were checked. Afterward, all predictors and moderators were mean-centered. This simplifies the interpretation of interaction effects: all coefficients account for respondents who score average on the predictor variables. Subsequently, interaction variables were created to test moderation effects. All hypotheses, the moderating role of previous experience on the relationship between WSD and BI, and the moderating role of age in the relationship between LOP and BI were tested with regression analyses. First, the traditional UTAUT variables were included as independent variables (PE, EE, SE). Second, age and experience were added as interaction variables. Third, we included the new variables WSD, LOP, trust, and the interaction variables (WSD, LOP, trust, and gender identity). This enabled a comparison between the initial UTAUT and the extended model. To answer the RQs with gender identity, dummy variables for gender identity were created (i.e., female, male, trans, non-binary) with female participants as the reference group. Next, a linear regression model was conducted, in which only PE, EE, SI, WSD, LOP, trust, the dummy variables for males, trans and non-binary individuals, and lastly the interaction variables for the respective predictor*gender identity effects were included.

4 Results

4.1 Sample Characteristics

Appendices 3 and 4 show the sample characteristics. Ages ranged from 16 to 59 years (*M* = 24.69; *SD* = 7.28). For gender identity, the largest category was female (43,60%, *n* = 133). 10,80% specified their gender identity in a separate text field. There, common answers were "Agender", "Genderfluid" and "Questioning". When it comes to previous experience with chatbots, respondents had the most experience (= used a chatbot very often, often or sometimes) with customer service chatbots (39,70%) and social messaging chatbots (22,60%), followed by healthcare chatbots (7,60%). Furthermore, most participants coped with mental health issues without receiving professional help (39,70%). Remarkably, only 12,80% stated to not cope with mental health issues at all.

Regarding respondents' level of education, the largest category was "completed upper secondary level" (34,80%).

4.2 Model Fit and Hypothesis Testing

Main Effects. The extended regression model with BI to use a mental health chatbot as dependent variable, with PE, EE, SI, WSD, LOP and Trust as independent variables and with age and previous experience as moderators was significant, $F(31, 304) = 20.17$, $p < .001$, and explained 69,60% of variance in BI to use a mental health chatbot. It also demonstrated a slightly better fit than the initial UTAUT, where only PE, EE and SI were considered as predictors, $F(16, 304) = 35.91$, $p < .001$, $R^2 = 66.60\%$ (see Appendix **5**). The extended regression model can therefore be used to predict the BI to use a mental health chatbot among the LGBTQIA+ population.

Only the effects for PE, EE, SI and WSD were significant. PE showed a significant, strong association with BI ($b = 0.67$, $t = 11.70$, $p < .001$, 95% CI [0.56, 0.79]). This indicates that people who believe that a mental health chatbot will help them increase their mental wellbeing, have a higher intention to use a mental health chatbot. Similarly, SI, $b = 0.18$, $t = 3.29$, $p = .001$, 95% CI [0.07, 0.28] showed a significant, weak association with BI. Hence, people who are more influenced by their social environment have a higher intention of using one. WSD showed a significant, weak association with BI ($b = 0.21$, $t = 3.69$, $p < .001$, 95% CI [0.10, 0.32]). We therefore found support for H1, H3 and H4.

Surprisingly, EE showed a weak, negative relationship (b = -0.14, t = -2.40, p = .017, 95% CI [0.08, 0.29]), which is opposed to what we expected. This indicates that, the more people perceive a mental health chatbot as easy to use, the lower is their intention to use such a chatbot. We therefore reject H2. Further, the results show that LOP ($b = 0.03$, $t = 0.91$, $p = .362$, 95% CI [-0.04, 0.11]) and Trust ($b = -0.03$, $t = -0.42$, $p = .672$, 95% CI [-0.14, 0.09]) are no significant predictors of chatbot usage. Thus, H5 and H6 were rejected.

Moderating Effects. In terms of interaction effects, we found only three weak, significant interaction effects. Firstly, the effect of SI on BI is moderated by previous experience with healthcare chatbots ($b = -0.16$, $t = -2.14$, $p = .033$, 95% CI [-0.31, -0.01]). This means that the effect of SI on BI becomes weaker the more experience LGBTQIA+ individuals have with healthcare chatbots. However, this is only the case for previous experience with healthcare chatbots. Previous experience with customer service or messaging chatbots were no significant moderators. Thus, we found partial support for H3b.

Secondly, the effect of WSD on BI seems to be very weakly moderated by age ($b = -0.02$, $t = -2.43$, $p = .016$, 95% CI [-0.04, -0.004]). As hypothesized, the effect is stronger for younger compared to older LGBTQIA+ individuals. H4a was therefore supported.

Thirdly, the relationship between LOP and BI was significantly and weakly moderated by gender identity, where the effect seems to be stronger for male individuals (b = 0.19, t = 2.09, p = .037, 95% CI [0.01, 0.36]) than for females (RQ4).

All other interactions turned out to be insignificant, which means H1a, H2a, H2b, H3a, H5a, H6a and H6b are rejected. In addition, previous experience with a chatbot is not a significant moderator for the relationship between WSD and BI (RQ2), and we did not find support for any other moderating effects of gender identity (RQ3, RQ4, RQ5). Figure 1 shows the significant relationships in the extended model.

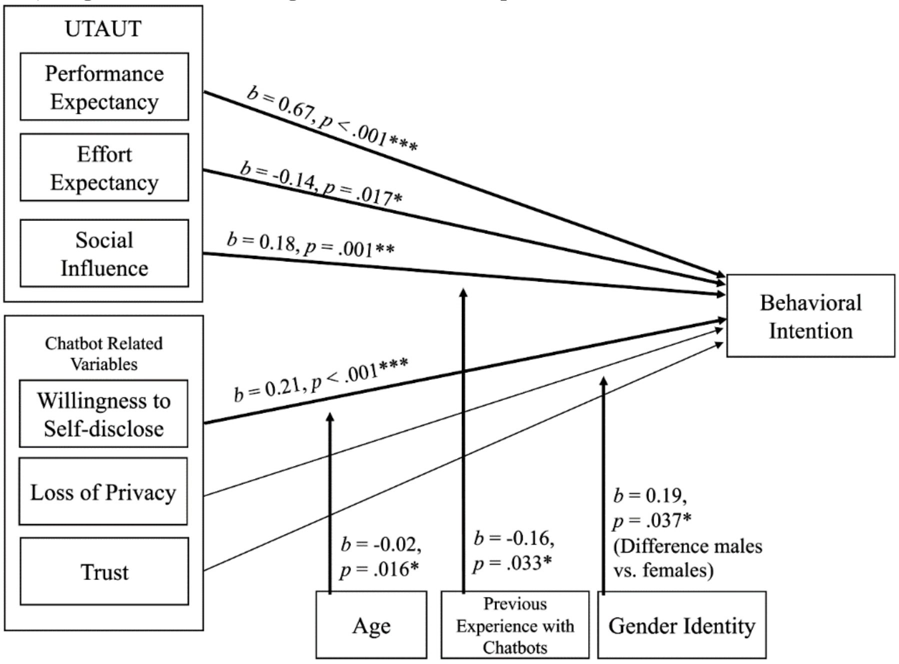

Fig 1. Significant relationships in the extended model

5 Discussion

This study aimed to take a critical perspective on the UTAUT by exploring whether it can be tested and extended in the context of mental health chatbot usage intention among LGBTQIA+ individuals. Through integrating the chatbot-specific variables willingness to self-disclose (WSD), perceived loss of privacy (LOP), and trust, and by considering gender identity, we were able to demonstrate that the extended UTAUT provides a better understanding of mental health chatbot usage intention among LGBTQIA+ individuals than the original model. Our findings do not only contribute to more inclusive technology acceptance models and the generalizability of the UTAUT, but also give valuable insights into which aspects influence the intention to use a mental health chatbot among LGBTQIA+ individuals.

In the current survey, performance expectancy (PE), Social Influence (SI) and WSD significantly predicted behavorial intention (BI) to use a mental health chatbot. Unsurprisingly, PE has shown to be the strongest positive predictor. PE has repeatedly been an important predictor for technology acceptance in previous research [3, 56, 60]. Hence, the belief that a mental health chatbot would improve their mental health seems to be a crucial driver for the BI to use a mental health chatbot among LGBTQIA+ individuals and should be highlighted in future chatbot interventions. Additionally, in line with prior research, the more a LGBTQIA+ individual believes that their social environment thinks they should use a mental health chatbot (SI), the higher is their BI [56, 62]. This effect seems to be stronger for less experienced people, which means that particularly when individuals have little experience, their social environment can have a significant impact on their BI to use a mental health chatbot. It is worth noting that the effect of SI on BI was very weak and, considering the strong community feeling of LGBTQIA+ individuals, we expected this effect to be stronger. Especially since a study by Fish and colleagues demonstrated that emotional and mental health topics were the most popular themes discussed in a chat-based Internet community support programme [18], thus LGBTQIA+ individuals are generally willing to discuss mental health problems with their peers. It might be that the usage of mental health chatbots is not as widespread as online communities [41] and that therefore SI is less important for the BI to use mental health chatbots. Overall, for future interventions, developers should emphasize the potential benefits mental health chatbots have to improve mental health issues among LGBTQIA+ individuals. In addition, social influence and community aspects should be taken into account, and people's willingness to self-disclose should also be considered as a crucial determinant for mental health chatbot usage intention.

We did not expect the negative relationship between effort expectancy (EE) and BI. The easier the usage of a mental health chatbot seems, the lower is LGBTQIA+ individuals' intention to use it. This negative direction is contradicting existing literature. Some studies found a significant relationship [3, 29, 61, 62] and others did not find a significant association due to common use of the technology under study [56]. However, all studies demonstrated a positive relation instead of a negative one. One explanation for the current findings can be that our results show a high mean EE, which suggests that many participants perceived a mental health chatbot as easy to use anyway. Another possible explanation could be that one of the contextual variables were suppressing the effect of EE since it only became significant when the other variables were added.

Surprisingly, two chatbot-related variables -perceived loss of privacy and trust- were no significant predictors of chatbot usage intention. Especially the results regarding trust do not align with prior research. For Liu and Tao, for instance, trust was the strongest predictor for BI to use a smart healthcare system [36]. Other studies have established trust as a crucial antecedent for chatbot acceptance [43-44]. A plausible explanation could be that LOP and trust did not directly affect BI to use a mental health chatbot, but indirectly via WSD. Schroeder and Schroeder found that trust positively influences WSD to a chatbot [51]. Similarly, lower privacy concerns seem to increase trust in chatbots [24]. Since WSD directly influenced BI, future studies may consider LOP as antecedent of trust, and trust as predictor of WSD rather than direct predictors of BI.

Moreover, this paper emphasized the importance of including gender identity into the UTAUT. Interestingly, the study did not find support for substantial differences among gender identities. Apparently, LGBTQIA+ regardless of their gender identity, perceive mental health chatbots equally, even though transgender and non-binary individuals show a higher online behavior compared to female or male individuals [41]. Only the effect of LOP on BI was stronger for males than females. This is interesting, as prior research on online behavior revealed that women are more concerned about their privacy [27, 53]. But then again, gender differences measured with non-LGBTQIA+ samples may deviate from our sample. The present findings would suggest that future mental health interventions for LGBTQIA+ individuals do not need to consider different factors for respective gender identities —except stressing privacy protection more among male individuals—, but this seems overly simplistic. The blurring boundaries between gender identities that prevail in our current-day society do ask for an increased attention to this in chatbot research, especially when the technology relates to mental health.

In line with previous research, this study shows that age is a factor to keep taking into account. While the relationship between WSD and BI remains equal for older LGBTQIA+ individuals, younger individuals have a higher intention to use a mental health chatbot when their WSD is also high. However, our sample was quite young (Ø 24 years) and the amount of participants age >40 years was rather limited. Thus, future research needs to pay more explicit attention to the age factor.

5.1 Limitations and Future Research

One major issue regarding the survey was that participants did not interact with a mental health chatbot themselves. Unfortunately, it was not feasible to develop a properly functioning mental health chatbot in the available time frame, and using existing chatbots like Wysa would have created privacy issues by involving third parties. At the same time, 92% of the participants had never or rarely used a mental health chatbot before, and thus must have had a hard time imagining such an interaction, which could have led to imprecise answers. This problem was already raised during the pre-test, which is why we included a screen recording of a mental health chatbot conversation. Yet, we had no control over whether participants actually watched this video.

Secondly, actual usage of mental health chatbots was not included as a dependent variable. A follow-up study could let participants test a mental health chatbot and, at the end of the study, provide a link to the chatbot application free for them to use. Measuring the click rate may reveal insights into the actual usage of the chatbot and lead to more precise results.

Lastly, as this research topic has not been researched in depth so far, researchers should consider applying a qualitative research design to gain an in-depth understanding of LGBTQIA+ individuals' thoughts on mental health chatbots. Interestingly, especially on reddit, the recruitment text for this study caused elaborate discussions about whether individuals would use such chatbot or not.

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Appendix 1

Operationalization of predictors and behavioral intention

Variable	Items as used in previous literature [60, 15, 36]	Adjusted items used in the current study
Performance expectancy [60]	PE1: I would find the system useful in my job. PE2: Using the system increases my productivity. PE3: Using the system enables me to accomplish tasks more quickly. PE4: If I use the system, I will increase my chances of getting a raise.	PE1: I would find such a mental health chatbot useful in my daily life. PE2: Using such a mental health chatbot would improve my mental health. PE3: Using such a mental health chatbot would help me to improve my mental health more quickly. PE4: Using such a mental health chatbot improves my mental well-being.
Effort expectancy [60]	EE1: Learning to operate the system is easy for me. EE2: My interaction with the system would be clear and understandable. EE3: I would find the system easy to use. EE4: It would be easy for me to become skilful at using the system.	EE1: Learning how to use such a mental health chatbot is easy for me. EE2: My interaction with such a mental health chatbot would be clear and understandable. EE3: I would find such a mental health chatbot easy to use. EE4: It would be easy for me to become skilful at using such a mental health chatbot.
Social influence [60]	SI1: People who are important to me think that I should use the system. SI2: People who influence my behavior think that I should use the system. SI3: In general, the organization has supported the use of the system. SI4: The senior management of this business has been helpful in the use of the system.	SI1: People who are important to me think that I should use such a mental health chatbot. SI2: People who influence my behavior think that I should use such a mental health chatbot. SI3: In general, my social environment would support the use of such a mental health chatbot.
Willingness to self-disclose [15]	WSD1: During the conversation I was able to share personal information about myself. WSD2: During the conversation I felt comfortable sharing personal information. WSD3: During the conversation it was easy to share personal information.	WSD1: I feel I could share personal information about myself with such a mental health chatbot. WSD2: I feel I would be comfortable sharing personal information with such a mental health chatbot. WSD3: I feel it would be easy to share personal information with such a mental health chatbot.

	WSD4: During the conversation I felt that I could be open.	WSD4: I feel that I could be open during a conversation with such a mental health chatbot. WSD5: How likely are you to confide in an anonymous chatbot for mental health issues?
Perceived loss of privacy [36]	LOP1: I am concerned that smart healthcare services will collect too much personal information from me. LOP2: I am concerned that smart healthcare services will use my personal information for other purposes without my authorization. LOP3: I am concerned that smart healthcare services will share my personal information with other entities without my authorization.	LOP1: I am concerned that such a mental health chatbot will collect too much personal information from me. LOP2: I am concerned that such a mental health chatbot will use my personal information for other purposes without my authorization. LOP3: I am concerned that such a mental health chatbot will share my personal information with other entities without my authorization.
Trust [36]	TRU1: Smart healthcare services are dependable. TRU2: Smart healthcare services are reliable. TRU3: Overall, I can trust smart healthcare services.	TRU1: Such a mental health chatbot is dependable. TRU2: Such a mental health chatbot is reliable. TRU3: Overall, I can trust such a mental health chatbot.
Behavioral intention [60]	BI1: I intent to use the system in the next <n> months. BI2: I predict I would use the system in the next <n> months. BI3: I plan to use the system in the next <n> months.	BI1: I intend to use such a mental health chatbot in the future. BI2: I will try to use such a mental health chatbot in my daily life. BI3: I plan to use such a mental health chatbot frequently.

Appendix 2

Eigenvalues, explained variance, Cronbach's α, means and standard deviation of main variables

Variable	Eigenvalue	% of Variance	Cronbach's α	Mean	SD
Performance expectancy	3.43	85.65%	.94	4.12	1.43
Effort expectancy	2.69	67.34%	.83	5.23	1.11
Social influence	2.22	73.98%	.81	3.44	1.23
Willingness to self-disclose	3.94	78.82%	.93	4.10	1.62
Loss of privacy	2.78	92.60%	.96	4.81	1.70
Trust	2.25	74.88%	.83	4.16	1.31
Behavioral intention	2.73	91.13%	.95	3.37	1.55

Note. Factor analysis with direct oblimin rotation was used; M and SD refer to the mean variables.

Appendix 3

Characteristics of the sample (N = 305)

Characteristics	n (%)
Age	
16-23	157 (51,5%)
24-30	89 (29,2%)
31-35	37 (12,2%)
36-40	10 (3,3%)
>40	12 (3,8%)
Gender Identity	
Male	67 (22,0%)
Female	133 (43,6%)
Non-Binary	54 (17,7%)
Transgender	13 (4,3%)
Intersex	0 (0%)
Other	33 (10,8%)
Level of Education	
No schooling completed	3 (1,0%)
Lower secondary level	31 (10,2%)
Upper secondary level	106 (34,8%)
Vocational training	13 (4,3%)
Bachelor’s or equivalent	96 (31,5%)
Master’s or equivalent	36 (11,8%)
Doctoral or equivalent	6 (2,0%)
Other	9 (3,0%)
Mental Health Issues	
Yes, receive professional help	94 (30,8%)
Yes, do not receive professional help	121 (39,7%)
No	39 (12,8%)
I am not sure	51 (16,7%)

Appendix 4

Frequency distribution for previous experience with chatbots (N = 305)

Type of Chatbot	Never	Rarely	Sometimes	Often	Very often
Customer service chatbots	82 (26,9%)	102 (33,4%)	97 (31,8%)	17 (5,6%)	7 (2,3%)
Healthcare chatbots	224 (73,4%)	58 (19,0%)	15 (4,9%)	6 (2,0%)	2 (0,7%)
Social messaging chatbots	152 (49,8%)	84 (27,5%)	46 (15,1%)	12 (3,9%)	11 (3,6%)

Appendix 5

Comparison of regression models to predict BI of mental health chatbot usage

	Behavioral Intention to Use Mental Health Chatbots	
	UTAUT model	Extended model
Constant	3.36***	3.35***
Performance expectancy	0.75***	0.67***
Effort expectancy	-0.08	-0.14*
Social influence	0.25***	0.18**
Willingness to self-disclose		0.19**
Perceived loss of privacy		0.04
Trust		-0.01
R^2	0.67	0.70
F	35.91***	20.17***

Note. * p <.05, ** p <.01, *** p <.001.