

HUMAN MACHINE COMMUNICATION: LEVERAGING AI CHATBOTS FOR SEXUAL AND REPRODUCTIVE HEALTH MANAGEMENT

by

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(Under the Direction of SOROYA JULIAN MCFARLANE)

ABSTRACT

This dissertation investigates how sexual and reproductive health (SRH) chatbots can be optimized to enhance health management among young adults. Utilizing a mixed-methods approach, this study integrates the Health Belief Model (HBM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Computers as Social Actors (CASA) framework to identify motivational, functional, and interactional factors that predict behavioral intentions to use SRH chatbots to manage SRH. The quantitative study surveyed 1,200 U.S. participants and validated a robust theoretical model and revealed the relationships between key variables and chatbot use intentions. Subgroup analysis highlighted that LGBTQ+ individuals value anonymity, empathy, and judgment-free communication, reinforcing the importance of inclusivity in chatbot design. The qualitative study involved co-creation workshops and an open-ended survey to explore user perceptions of empathetic and non-empathetic message designs. Findings revealed that empathetic messaging fosters emotional safety and trust, while concise, factual language enhances credibility. The study demonstrated that tailoring chatbot messaging and user interface features enhances engagement, user satisfaction, and self-disclosure. Ultimately, this dissertation contributed to the growing body of human-machine communication (HMC) and health communication research by proposing an integrated theoretical framework

and offering practical recommendations for ethical, culturally sensitive, and user-centered chatbot design.

INDEX WORDS: Human-Machine Communication, Sexual and Reproductive Health, Chatbots, Digital Health, Empathy, Self-Disclosure, LGBTQ+ Health, eHealth Literacy, Health Belief Model, UTAUT, CASA Framework, Mixed Methods Research, Anthropomorphism, Health Communication

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DEDICATION

To my younger brother, my forever guardian angel in heaven. Your light continues to guide me through the darkest hours and brightest moments. Though your footsteps no longer echo beside mine, your love walks with me in every step. This journey, this work, this milestone, I carry your spirit in all of it. You are my reminder of resilience, my reason to reach higher. This is for you.

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CHAPTER 1

Chapter Overview

In recent years, the integration of technology into healthcare interventions has garnered considerable attention as a promising avenue for improving health outcomes and promoting positive behavior change (Martinengo et al., 2022). Among these innovations, chatbots have emerged as powerful tools for disseminating tailored health information and offering emotional and behavioral support (Laymouna et al., 2024). This chapter introduces the central aim of the dissertation: to explore the potential of chatbot engagement as a mechanism for promoting sexual and reproductive health (SRH) management among young adults. It highlights the relevance of digital interventions, particularly SRH chatbots, in providing an accessible, confidential, and user-centered resource. The chapter concludes by stating the research objectives and offering a rationale for the mixed-methods approach used to assess the design and impact of empathetic SRH chatbots.

Chapter 2: Literature Review

This chapter reviews the scholarly landscape surrounding human-machine communication (HMC), with an emphasis on its applications in healthcare and, more specifically, in sexual and reproductive health contexts. It begins by charting the evolution of HMC, from early examples like ELIZA to contemporary AI-driven conversational agents and explains how these technologies have become increasingly capable of simulating human interaction. The chapter then shifts focus to the use of chatbots in health communication, outlining their functional benefits, such as anonymity, scalability, and responsiveness. Particular

attention is given to the role of empathetic messaging and anthropomorphic design in promoting trust, self-disclosure, and user satisfaction. Challenges such as the Uncanny Valley effect, concerns over privacy and data security, and digital health literacy are also explored. Finally, the chapter identifies gaps in existing literature, including a lack of integrated theoretical models and inclusive designs tailored to LGBTQ+ users, thereby justifying the need for this study.

Chapter 3: Theoretical Framework

This chapter presents the theoretical underpinnings of this dissertation by proposing an integrated model with pertinent factors from the Health Belief Model (HBM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Computers Are Social Actors (CASA) framework. HBM provides health-related attributes, such as perceived benefits, barriers, and self-efficacy, which are used to predict behavioral intentions. UTAUT contributes functional attributes like performance and effort expectancy, as well as social influence, which assesses the usability and motivation to adopt chatbot technologies. CASA offers interactional insights by examining how anthropomorphic features and empathetic messaging affect user perceptions and engagement. This conceptual integration allows for a multidimensional exploration of chatbot adoption, bridging health psychology, technology acceptance, and interpersonal communication. Digital health literacy is introduced as a moderating variable, offering insights into how users' competence with digital tools influences their engagement with chatbots. This chapter concludes with a visual representation of the proposed theoretical model and a discussion of its applicability to SRH chatbot use.

Chapter 4: Methodology

This chapter outlines the mixed-methods research design used to investigate the effectiveness and user perception of SRH chatbots. The first study is a quantitative national survey involving 1,200 participants aged 18-32, assessing behavioral intentions and the predictive power of the integrated theoretical model. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), this study evaluates the impact of constructs such as anthropomorphism, self-efficacy, and performance expectancy on chatbot engagement. It also includes a subgroup analysis of LGBTQ+ users to uncover unique motivational and barrier factors. The second study employs qualitative methods, including co-creation workshops and open-ended surveys, to explore users' perceptions of empathetic versus non-empathetic chatbot message designs. This phase utilizes participatory design principles, involving Planned Parenthood's digital product team in creating realistic message prototypes. Thematic analysis is then used to interpret user feedback, offering nuanced insights into how empathy, tone, and personalization affect trust, self-disclosure, and willingness to engage. The methodology chapter provides a robust foundation for understanding the multidimensional nature of human-chatbot interaction.

Chapter 5: Quantitative Study Results (General Population)

This chapter presents the results of the national survey, testing an integrated theoretical framework. This study examined predictors of behavioral intentions to use a SRH chatbot among a sample of 1,200 young adults in the United States. Results indicated strong support for the proposed integrated model, with significant relationships observed between anthropomorphism and performance expectancy, as well as between performance expectancy and behavioral

intentions. Self-efficacy emerged as one of the strongest predictors influencing chatbot engagement. The model explained a substantial proportion of variance in users' intentions to use the chatbot for SRH management. Mediation analyses further highlighted that anthropomorphic features influence behavioral intentions through effort expectancy. These results suggest that health, functional, and interactional attributes play a pivotal role in motivating chatbot use, reinforcing the value of an integrated theoretical approach. The chapter concludes by discussing the implications of these findings for chatbot design and health interventions targeting the general young adult population.

Chapter 6: Quantitative Study Results (LGBTQ+ Subgroup)

This chapter focuses on the results of a subgroup analysis conducted within the quantitative study to explore behavioral intentions among LGBTQ+ participants. Recognizing that LGBTQ+ individuals often face unique barriers when accessing sexual health resources, this chapter investigates whether their motivations and experiences differ from the general population. Results revealed that LGBTQ+ users placed greater emphasis on factors such as perceived empathy, anonymity, and judgment-free communication. Social influence played a smaller role compared to the general population. Notably, digital health literacy emerged as a particularly salient moderator in this group, strengthening the relationship between self-efficacy and intentions to use the chatbot. The findings emphasize the need for inclusive, identity-affirming chatbot designs and communication strategies that resonate with LGBTQ+ users. This chapter contributes to the limited but growing body of research on health technology use among marginalized populations and calls for the development of culturally sensitive tools to promote health equity in digital interventions.

Chapter 7: Qualitative Study Results

This chapter presents findings from the second study, which employed qualitative methods to explore user perceptions of chatbot message design, particularly focusing on empathetic versus non-empathetic communication styles. Participants reviewed a series of message prototypes co-designed with Planned Parenthood stakeholders and provided feedback through open-ended surveys. Thematic analysis revealed that empathetic messaging—characterized by warm tone, emotional validation, and use of emojis—enhanced users' sense of psychological safety and trust. Participants appreciated messages that balanced compassion with factual clarity, noting that overly scripted or robotic language reduced credibility and engagement. However, some participants expressed discomfort when chatbot messages appeared too human-like, aligning with the Uncanny Valley effect. Customizability, autonomy in conversation flow, and perceived authenticity were key themes that emerged as critical to sustained engagement and willingness to disclose sensitive information. This chapter highlights the importance of message design in shaping human-machine communication and provides actionable insights for creating emotionally intelligent, user-centered chatbot interactions that foster trust and self-disclosure in SRH contexts.

Chapter 8: Conclusion

This chapter concludes the dissertation by synthesizing the core findings of this multi-phase mixed-methods study on AI-powered sexual and reproductive health (SRH) chatbots. Anchored in an integrated framework combining the Health Belief Model (HBM), UTAUT, and the CASA paradigm, this chapter highlights the dissertation's theoretical and practical contributions to health communication and human-machine interaction. The chapter first revisits how the validated theoretical model advances our understanding of young adults' behavioral

intentions to use SRH chatbots. It then details key subgroup insights, specifically the distinct needs and motivators of LGBTQ+ users, pointing to the importance of intersectionality and digital health literacy in inclusive design. The chapter also underscores the critical role of empathetic message design, personalization, and co-creation in enhancing trust and user experience, while cautioning against emotional overreach due to the Uncanny Valley effect. These findings coalesce into a set of actionable design principles for equitable, user-centered chatbot development. The conclusion calls for future research to explore longitudinal engagement, real-time adaptation, and culturally responsive design.

CHAPTER 2

Literature Review

Human-Machine Communication

Digital communication technologies have become an integral part of our everyday life (cite). Some people may start their day with Amazon's "Alexa" or Apple's "Siri", relying on these virtual assistants for news, weather forecasts, and to-do lists (cite). These interactions show the growing presence of human-machine communication and how the use of these technological systems have become seamlessly integrated in our lives for added convenience. Beyond convenience, these technologies can understand human language communicated to them through voice recognition or text inputs, processing and responding to such information by mimicking human communication styles. As technology continuously improves, the characteristics of these machines are elevated, making them not just a functional tool but also a digital companion and resource that can be used for decision-making and task management.

Human-machine communication (HMC) has been historically rooted in understanding the ways humans are able to interact with a form of technology through sending and receiving messages as compared to traditional interpersonal communication between two or more humans (Guzman & Lewis, 2019). Early researchers in this field such as J.C.R Licklider brought the vision of "man-computer symbiosis" to the forefront, paving the understanding of how humans and machines could communicate and develop a common understanding despite the vast language barriers between them (Grudin, 2012). This issue of language or the mismatch between human and computer language has been reduced with the development of natural language processing (Chowdhary & Chowdhary, 2020). Researchers also started viewing machines as active participants in communication through the development of Joseph Weizenbaum's ELIZA

program in 1966 (Kratel, 2022). ELIZA was a pioneer in natural language processing and the first chatbot to provide conversational output for its users (Kratel, 2022). The system stimulated a conversation with a human therapist, paving the way for technology in health communication (Kratel, 2022). This two-way communication between humans and machines laid the foundation in exploring the potential and extent to which machines could stimulate human-like interactions, influence decision-making processes, and facilitate meaningful communication exchanges.

HMC sits in a unique interdisciplinary crossroad between communication technology and human behavior. It has been a growing area of research examining how humans interact with technology as communicative subjects as well as benefits and potential challenges (Greussing et al., 2022). Earlier HMC work often used traditional models such as the Shannon-Weaver Communication Model (Al-Fedaghi, 2012), where focus was placed on linear forms of communication between humans, emphasizing the roles of sender, receiver, channels and environmental noise. However, with the advancement of technology such as using artificial intelligence (AI), more attention has shifted towards examining the interactive and reciprocal nature of communication between humans and machines (Magni et al., 2024). For example, Westerman and colleagues (2020) showed in their conceptual paper the growing significance of AI in HMC and highlighted the need to understand how humans interact with such machine systems. They pointed out the importance of integrating HMC with other existing theories and frameworks such as interpersonal theories, health theories or interactional theories such as the Computers Are Social Actors (CASA) to provide more robust understanding towards both HMC and human-human communication (Westerman et al., 2020). This shift recognizes that HMC is not simply a transactional exchange of information but a dynamic and evolving interaction

between humans and machines, shaping perceptions, trust, and meaningful engagement with technology (Asif & Gouqing, 2024).

HMC in Health

While HMC has been used in a gamut of interdisciplinary fields, the health domain experienced a significant boost in HMC following the onset of the Covid-19 pandemic (Vargo et al., 2021). As the novel coronavirus mandated isolation and reduced access to in-person health resources, many services migrated to online platforms. Furthermore, the strain on the healthcare workforce catalyzed the shift of many services towards digital solutions to stay efficient (Filip et al., 2022). Machines or robots were used for Covid-19 diagnoses and testing, for example, Lifeline Robotics in Denmark, developed a robot collecting throat swabs without increasing the workload on healthcare professionals and mobile robots with high-accuracy thermometers were dispatched to monitor individuals showing Covid-19 symptoms in highly populated areas (Shen et al., 2020). These data were then communicated to healthcare professionals reducing the need for unnecessary contact and increasing efficiency of diagnoses curbing the rapid spread of the virus (Shen et al., 2020).

Social robots were also used as a functional and educational resource during the pandemic. Loneliness due to isolation increased significantly as part of social distancing measures to reduce the spread of the virus (Odekerken-Schröder et al., 2020). Aymerich-Franch and Ferrer (2022) revealed that social robots provided humans with three strategic roles during the Covid-19 pandemic. The roles included a liaison role where social robots acted as a bridge in tasks that would require human-human interaction, safeguarding where social robots provided information and education on reducing the spread of the coronavirus and well-being coaches where the social robots provided social support, comfort and entertainment to reduce loneliness

during isolation (Aymerich-Franch & Ferrer, 2022). An example of this form of technology includes Q-Bot a chatbot launched by the Centers for Disease Control and Prevention (CDC) as an informational and social communication tool to educate the public on Covid-19 issues (Tiwari, 2020).

Fast forward five years post pandemic, we are still relying heavily on these tools to check for symptoms, schedule health checkups or search for health information. The development of human machine technology-based approaches has been highlighted as a key contributor to the transformation of healthcare for the better (Jazieh & Kozlakidis, 2021). However, there remains a need for deeper exploration into the multidimensional nature of HMC specifically in examining the factors that could influence communication effectiveness and user engagement as well as how advancements could be made to reduce barriers during interaction (Madanian et al., 2023; Mumtaz et al., 2023).

Chatbots

A popular HMC tool used in the health domain is a chatbot as seen in a scoping review revealing its increased usage post Covid-19 pandemic (Tzelios et al., 2022). Chatbots are conversational agents developed using AI-enabled natural language processing (NLP) to mimic human conversations (Wilson & Marasoiu, 2022). They have become an increasingly common tool connecting users with resources as well as providing different types of support by tailoring responses according to users' needs (Laymouna et al., 2024). Since the first known chatbot ELIZA and the development of ALICE (Artificial Linguistic Internet Computer Entity) which formed the foundations of pattern-matching algorithms-Artificial Intelligence Markup Language (AIML) (Adamopoulou & Moussiades, 2020), technological advancements have paved the way for modern and more evolved versions of language recognition. With the rise of AI, machine

learning, deep learning and the development of multimodal capabilities, chatbots have evolved from an informational tool to a sophisticated digital concierge providing a more interactive and personalized experience in recent years (Wah, 2025). Many chatbots are categorized based on their underlying technology as this affects the way they understand and communicate with human users (Adamopoulou & Moussiades, 2020). Rule-based chatbots function on simply predefined decision-trees or matching user input with predetermined answers, this type of chatbot is often limited in its capabilities to understand complex language or mimic human conversations cohesively (Thorat & Jadhav, 2020). Newer chatbots are more interactive and leverage AI by using a retrieval-based approach getting data from a larger database, tapping into the extensive abilities of machine learning or using NLP and large language models (LLMs) to interpret texts accurately and communicate with users by generating human-like conversations (Chakraborty et al., 2023).

Chatbots for Health Communication

In the health space, chatbots have grown to become assistive resources for a wide range of health management tasks. A rapid review found that chatbots were primarily used for the delivery of remote health services across different health sectors which included supporting patients through health management, education, and promoting good health behaviors (Laymouna et al., 2024). The review showed that chatbots were actively used as administrative assistants for healthcare providers such as streamlining appointment scheduling (Laymouna et al., 2024). Additionally, the review underscored the transformative nature of chatbots in healthcare and its potential to improve health management and behavioral change (Jadczyk et al., 2021). For example, in areas such as mental health, SRH, and disease management, chatbot

interventions have demonstrated capabilities in fostering a safe and stigma-free environment that encourages users to disclose sensitive information when seeking help (Laymouna et al., 2024).

A separate scoping review identified the significance of health-related chatbots in promoting health and well-being, stating that anthropomorphic cues enhanced user experience, build rapport and engagement, and increased satisfaction (Xue et al., 2023). The review showed that building relational capacity through communication strategies such as having empathetic social dialogues between humans and machines increased feelings of social and emotional support and was associated with subsequent desirable health behavioral outcomes (Xue et al., 2023). Incorporating empathetic message styles (Juquelier et al., 2025) alongside other chatbot features that build trust and increase user engagement and satisfaction. This reinforces the potential of chatbots as a health resource to supplement traditional healthcare environments (Pereira & Diaz et al., 2019). As technology continues to advance, there has been more attention towards exploring how human-chatbot interactions can be improved through exploring humanistic features of chatbots and chatbot message design to create engaging and supportive digital health experiences (Balaskas et al., 2022; You et al., 2023; Kefi et al., 2024). These capabilities also hold the promise of addressing health disparities by providing communities with accessible and culturally tailored care for populations that often face discrimination in healthcare, transforming the landscape of digital health engagement and health promotion (Nadarzynski et al., 2024).

Chatbot Message Design

Empathy is a key concept when testing anthropomorphism in health chatbots as it fosters trust, relatability and user comfort particularly when interacting with sensitive SRH information (Shen et al., 2024). Empathetic communication styles are important in digital health

interventions as they create less threatening or intimidating environments when discussing health issues. Empathetic communication can help to validate emotions through compassionate and understanding language, mirroring supportive health communication styles (Lipp et al., 2016).

While empathy is an important construct, there have been mixed effects when using empathy for digital health interventions (Terry & Cain, 2016). A study conducted by Seitz (2024) showed that there is a threshold to which empathy is appreciated by users. Beyond that, empathy can come across as inauthentic and reduces users' trust when interacting with the chatbot (Seitz, 2024). Given the multidimensionality of empathy as a concept, the study also showed that while empathy of any kind increased trust and use intentions, there was a need to consider "perceived authenticity" to ensure that human chatbot interactions were not considered ingenuine (Seitz, 2024).

The Uncanny Valley effect stipulates that when digital products act too much like real human beings, a feeling of eeriness occurs reducing likability and motivation to interact with the product (Ciechanowski et al., 2018). A study conducted by Song and Shin (2022) about the humanization of chatbots on perceptions of eeriness, trust and behavioral intentions found that overly humanizing chatbots increased user's feelings of eeriness and negatively influencing their trust and intentions to use the chatbot (Song & Shin, 2022). These findings highlight the need for a delicate balance when incorporating human characteristics to digital products, without triggering feelings of inauthenticity and eeriness.

Emojis to Enhance Empathy

The use of emojis has been a device used to increase the feeling of empathy and warmth in human chatbot interactions (Yu and Zhao et al., 2024). Emojis are characterized as a form of emotional expression aiding communication between humans and technology (Elder, 2018).

They serve as visual cues to compensate for the lack of nonverbal communication in text-based communication, conveying tonality, and emotional sentiments (Sergeant, 2019). Research has shown that emojis accentuate empathy in interactions and creates a more personable and interactional dialogue (Erle et al., 2022).

In the context of digital health interventions, the strategic use of emojis could help to convey a supportive and understanding environment where self-disclosure could be encouraged as there is a reinforced sense of reassurance and psychological safety (Van Dam et al., 2019). However, other studies have cautioned that emojis are highly context-dependent and inappropriate use can result in reduced satisfaction or source credibility when communicating health information (Koch et al., 2023). Hence, there is a need to explore how emojis could be a supplemental feature to empathy or not when adapted meaningfully in HMC.

Self-disclosure

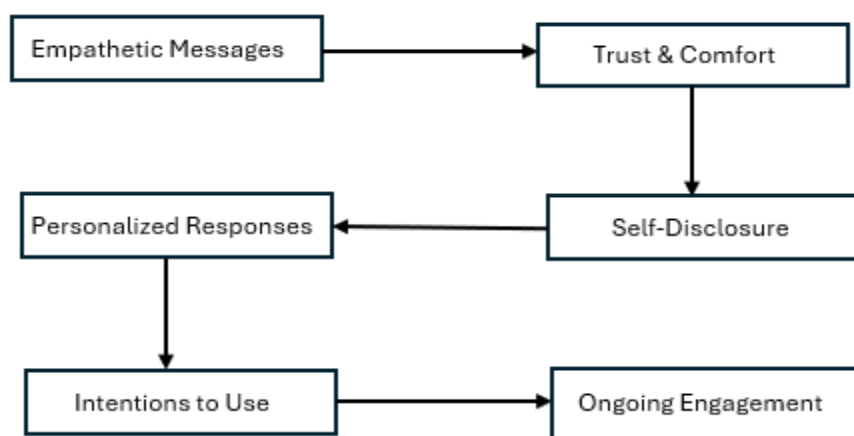
In HMC, self-disclosure is defined as the conversational act of willingly disclosing information about oneself with the dialogue system reciprocating and producing responses accordingly (Ravichander & Black, 2018). Self-disclosure from users plays an important role in HMC as it allows chatbots to provide personalized responses that are tailored to the user's specific needs, enhancing satisfaction, and making the interaction more relevant and valuable (Lappeman et al., 2023). When users reveal more health information, the chatbot will be able to use the data to deliver more relevant information. These personalized responses, in turn, strengthen the user's intentions to use the chatbot for health management by showcasing its utility and responsiveness. It also encourages a sense of being seen and heard, which is an important aspect in health communication (Brooks et al., 2019).

A HMC study conducted by Ho and colleagues (2018) explored how disclosing information to chatbots could improve emotional, psychological, and relational aspects for humans. The results supported the media equivalency hypothesis suggesting that humans experienced equal emotional support from chatbots as compared to humans (Ho et al., 2018). Popular social chatbots such as mental health chatbot Woebot presented itself as a virtual companion helping users suffering from depression or anxiety monitor their moods by encouraging self-disclosure (D'Alfonso et al., 2017). A different study by Croes and colleagues (2024) highlighted Derlega and Grzelak's functional theory of self-disclosure and how chatbots entail underlying functional mechanisms such as perceived anonymity and judgement-free interactions, creating conducive environments for self-disclosure and improvement of well-being (Croes et al., 2024).

This suggests that given the correct environment to stimulate disclosure, well-designed human-chatbot interactions could facilitate health management, reinforcing how chatbots could support health communication and user engagement. Once users are motivated to engage, ongoing interactions establish an iterative feedback loop where positive experiences further reinforce trust, comfort, and continued usage, creating a cycle of sustained engagement and user satisfaction (Borghouts et al., 2021). Figure 1 below illustrates this cycle.

Figure 1

Proposed Conceptual Model of Human Chatbot Communication



Sexual and Reproductive Health Chatbots

Health chatbots are a unique digital health intervention as they are convenient, largely accessible and foster a judgement-free environment creating a comfortable setting when sharing sensitive health information (Haque & Rubya, 2023). A recent realist synthesis showed that SRH chatbots could be a solution to provide nonjudgemental spaces for vulnerable SRH discussions especially for individuals who face stigma and discrimination (Mills et al., 2023). This synthesis also found that this underlying mechanism of chatbot technology has increased willingness for self-disclosure and has helped some users overcome shame and logistical barriers when seeking SRH information (Mills et al., 2023).

Nadarzynski and colleagues (2021) conducted a mixed-methods study exploring the experiences and perceptions of young adults utilizing a SRH chatbot. Their findings indicated that participants viewed SRH chatbots as a valuable resource for obtaining accurate information in a discreet and non-judgmental manner. Participants appreciated the anonymity afforded by the

chatbot, which facilitated open and honest discussions about sensitive sexual health topics that they might be hesitant to address with healthcare providers or peers (Nadarzynski et al., 2021). Moreover, the studies found that participants perceived the chatbot as a trustworthy source of information, highlighting its potential to bridge gaps in sexual health education and awareness among young adults (Berry et al., 2019; Lee et al., 2021). A case study by Wang and colleagues (2022) similarly examined SRH chatbot SnehAI, showcasing it as a trusted friend and mentor providing tailored and personalized educational content for users optimizing their HMC experience (Wang et al., 2022). Altogether, these findings show the transformative potential of SRH chatbots in providing judgment-free, supportive, and inclusive digital intervention for users to seek SRH resources.

Benefits of SRH Chatbots

When meaningfully designed, chatbots can provide a judgement-free, inclusive, and reliable SRH resource overcoming challenges young adults face when accessing SRH care. Advancements in HMC have allowed chatbots to convey information in a responsive and conversational way, using inclusive language and fostering a supportive anonymous environment (Mills et al., 2023). From a functional perspective, chatbots convey information in a conversational format, segmenting complex information into an easy to understand which is helpful especially for those with lower literacy levels or SRH awareness (Bickmore et al., 2016). Its anthropomorphic characteristics allow for engaging conversational strategies such as expressing empathy or concern through validating user emotions using familiar language (Rapp et al., 2021).

Beyond an informational tool, SRH chatbots function as a digital health concierge, signposting users to appropriate SRH services beyond the chatbot (Nadarzynski et al., 2021).

This coincides with the “actionability” concept which is a key affordance for chatbots (Wang et al., 2022). Interactions with SRH chatbots can prompt users to take subsequent steps to manage healthcare such as visiting a recommended SRH clinic (Wang et al., 2022). This actionable step positions chatbots as the first point of contact, offering stigma-free information, and directing marginalized users such as LGBTQ+ users to affirming clinics that meet their needs (Mills et al., 2023). Taking tangible steps upon receiving information from the SRH chatbot could also encourage young adult users to shift from simply knowing to executing actions that could mitigate the spread of Sexually Transmitted Infections (STI s), leading to better SRH management (Mills et al., 2023).

Limitations of SRH Chatbots

While there are many benefits of using SRH chatbots, it is also important to consider the limitations it might entail. Health chatbots are a first step towards tangible action but they should be used in tandem instead of substitution with in-person professional care and advice if an intervention is needed (Laymouna et al., 2024). Users could face technical challenges when accessing the chatbot, showing the importance in considering the intuitiveness of the chatbot design to adapt to different user needs (Al-Shafei, 2024). Some SRH chatbots do not have inclusive features or assistive technology such as screen readers or text-to-speech functions, this may exclude individuals from vulnerable populations from receiving the critical health information they need (Mateos-Sanchez et al., 2022).

Given that sensitive information is shared by the user using chatbot technology, there is concern about privacy and data security (Li, 2023). With the evolving use of AI in health technology, there has been an urge for all health technology to comply with the Health Insurance Portability and Accountability Act (HIPAA) to promote additional guardrails and protect

sensitive health information (Li, 2015, 2023). Unlike traditional healthcare practices bounded by clear regulations and laws, health chatbots lack commonly accepted standardized regulations or ethical guidelines (Li et al., 2023). Furthermore, AI algorithm biases could accidentally reinforce harmful stereotypes perpetuating inequalities instead of mitigating them if the training data lacks inclusiveness and diversity (Ferrara, 2024).

Digital Health Literacy

As there is an increasing shift towards the use of technology for healthcare, it is crucial to understand how digital health literacy could impact the utilization or underutilization of digital health products such as SRH chatbots. Digital health literacy or e-health literacy is the ability for individuals to independently identify, understand, and appraise health information on electronic or digital sources (Cetin & Gumus, 2023). Many SRH chatbots use text-based interactions assuming that users are proficient in navigating these interfaces (Mills et al., 2023). Furthermore, technological barriers such as lack of accessibility and knowledge on how to use chatbots to seek health information or management can act as a deterrent (Aggarwal et al., 2023).

Users with low digital health literacy have increased risks of succumbing to misinformation and negative health outcomes (Taba et al., 2022). With higher levels of digital health literacy, users develop more self-efficacy and determination to engage with digital health products (Okan et al., 2023; Taba et al., 2022). Studies by several researchers have shown that individuals with higher levels of digital health literacy have higher competence in seeking appropriate and reliable health information and adopting health behaviors (Britt et al., 2017; Mitsutake et al., 2016; Rosaro et al., 2020). To maximize the effectiveness of SRH chatbots, it is essential to address such challenges to identify their impact on user engagement and provide

impactful solutions such as increased education that could improve user confidence when navigating such chatbots.

Engaging Young Adults

In 2021, the Centers for Disease Control and Prevention (CDC) reported that 50.5% of STI cases in the United States were among young adults 15-24 years old (CDC, 2023). Recent data indicates a concerning upward trend in STI rates among both male and female young adults, contributing to the overall increase in STI incidence in the United States (CDC, 2023). Some young adults lack the awareness of contraception or safe SRH practices while others experience challenges in accessing trustable SRH care catered to their individual needs (Ozdal & Demiralp, 2024).

Young adults are susceptible to various SRH challenges from many behavioral and socio-cultural reasons. From a behavioral perspective, young adults are more prone to risky sexual practices such as engaging in unprotected sexual intercourse (Caccamo et al., 2017). Socio-culturally, young adults are also known to underutilize sexual health services because of embarrassment, misinformation, and a lack of awareness about available resources and support (Nadarzynski, 2021). SRH services providing credible resources are not always readily available for young adults, especially those who were living in more conservative communities (White et al., 2018). The absence of comprehensive education also contributed to a lack of awareness regarding SRH resources (Miller et al., 2014) while unpleasant and judgement healthcare experiences where healthcare providers ignore the needs of young adults present an unsupportive attitude created further obstacles towards receiving personalized SRH care (Decker et al., 2021). As a result, many young adults underutilize SRH resources, thereby increasing their vulnerability to adverse health outcomes.

Marginalized LGBTQ+ Community

Within the young adult's population, LGBTQ+ individuals are disproportionately impacted by SRH issues such as gonorrhea and syphilis (CDC, 2023). LGBTQ+ young adults (18-24 years) have a high risk of contracting and transmitting STIs including HIV (CDC, 2023). According to the Sexual Information and Education Council of the United States (SIEC), several reasons such as gaps in comprehensive sexual education and non-inclusive state policies have prevented LGBTQ+ young adults from receiving equal and medically accurate sexual health resources, despite these young adults having more susceptibility towards sexual health risks (Rabbitte, 2020).

A systematic search by Castleton and colleagues highlighted the lack of information inclusivity in SRH toolkits, addressing the need to include more resources about LGBTQ+ SRH as this was not well represented in the toolkits they examined (Castleton et al., 2024). Similar barriers experienced included trouble seeking relevant or appropriate SRH information, communicating with healthcare professionals without judgment and having low perceived confidence in the ability of health providers to deliver equitable LGBTQ+ care (McIntyre et al., 2011; Safer et al., 2016). As a result, preliminary evidence from the Health Information National Trends Survey (HINTS) showed that individuals from sexual minority groups had a higher tendency to use digital interventions to seek tailored information compared to heterosexual individuals (94.2% vs. 79.5% respectively; $p < 0.001$) (Jabson et al., 2016). As a step towards seeking suitable and inclusive health resources, many LGBTQ+ individuals have turned to digital health interventions (Jabson et al., 2016) such as SRH chatbots.

Research Objectives

“Optimize to maximize” is the overarching goal of this dissertation. Given the potential SRH chatbots have that can benefit young adults, this dissertation explores how SRH chatbots can be maximized to achieve better outcomes for SRH management. SRH management is defined as the process of using SRH chatbots as a navigator to actively seek, engage, and apply information, services, or behaviors to make informed SRH decisions.

The first objective focuses on factors influencing intentions to use SRH chatbots for SRH management. This includes quantitatively testing a proposed theoretical model by integrating health, functional, and interactional theories to create a robust framework of motivation. This bridges the gap in HMC theoretical models exploring the intentions to use SRH chatbots.

The second objective is to identify how these motivational factors differ among the general population and members of the LGBTQ+ community, a disparity group often facing challenges accessing tailored judgement-free SRH services. Identifying unique barriers is crucial when developing an impactful and inclusive SRH resource.

The last objective is to qualitatively understand how HMC occurs through chatbot message design, focusing on the anthropomorphism characteristics of SRH chatbots and how that affects self-disclosure and user-engagement. While the user experience design encompasses a broad range of elements, this study deliberately focused on message design because it was the most direct component of HMC. This is important because chatbot message designs shapes user perceptions and willingness to interact with this health resource, potentially minimizing the underutilization of a helpful health management tool.

CHAPTER 3

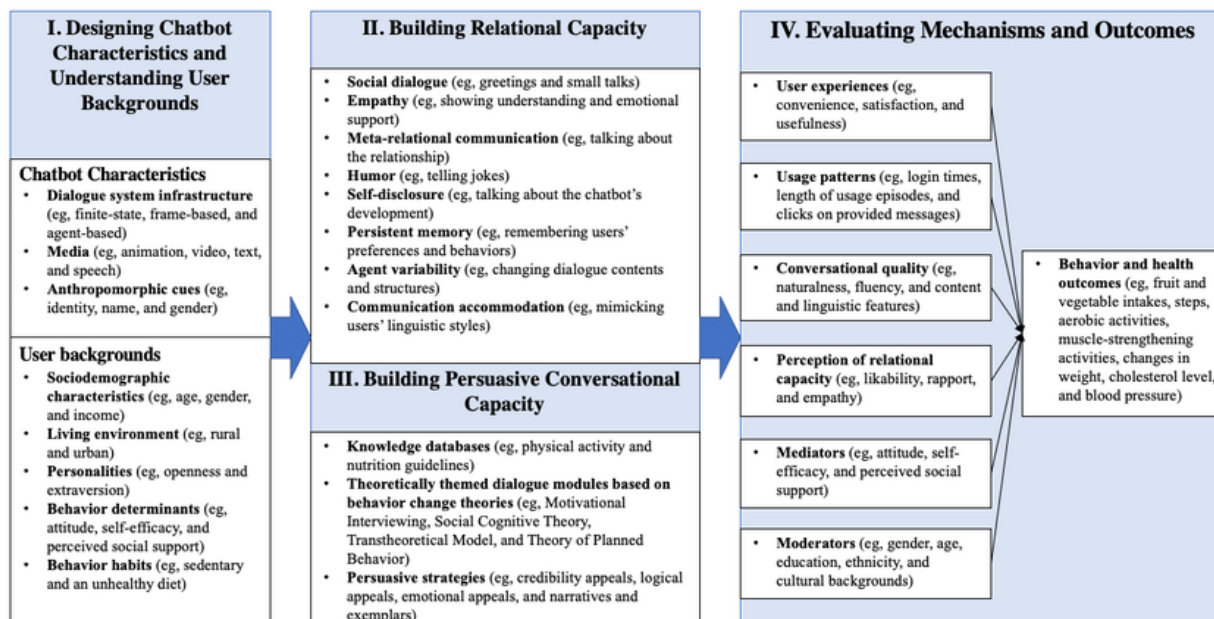
Theoretical Framework

In an era characterized by rapid technological advancements and growing concerns over public health equity, innovative digital solutions have emerged as a promising avenue for promoting accessible and tailored healthcare interventions. Health chatbots have garnered significant attention due to their efficacy and widespread acceptance among users seeking health resources (Balaji et al., 2022). However, several systematic reviews have highlighted that there were mixed reviews regarding feasibility, acceptability, and usability despite the high potential for chatbots to improve health outcomes and behavior change (Balaji et al. 2022; Mills et al., 2024). Specifically, systematic reviews within the field of SRH chatbots have underscored the absence of formal intervention evaluations conducted with standardized definitions or theoretical frameworks, leading to limitations in terms of generalizability and hindering the ability to draw robust conclusions when applying findings to diverse populations (Mills et al., 2023). Researchers emphasized the importance of subsequent efforts in incorporating relevant theoretical developments to accurately inform the future development and improvements of similar chatbots.

A review conducted by Zhang and colleagues (2020) found limited theoretical guidance and recommendations when developing and evaluating behavior change chatbots. Hence, they proposed the first “Artificial Intelligence Chatbot Behavior Change Model” (Figure 2) as a novel step to conceptualize and synthesize possible dimensions of chatbot features and evaluation mechanisms that could inform intervention designs and subsequent evaluations.

Figure 2

The Artificial Intelligence Chatbot Behavior Change Model (Zhang et al., 2020).



The Artificial Intelligence Chatbot Behavior Change Model (AICBCM) conceptualizes and assesses the different phases of chatbot development and evaluation. Behavior change chatbots are designed to alter users' particular behaviors by engaging in dialogues and providing information and persuasive messages (Zhang et al., 2020). The first phase of the model highlights the importance of understanding the user's background which involves factors such as social and behavioral determinants of health. These factors would be essential in the initial design phase of the chatbot. Analyzing the interface and feature characteristics of the chatbot would also be key in this stage. In the next stages, the chatbot should be further developed by building relational and persuasive conversations. Finally, multiple factors predict predictors of behavioral and health outcomes, such as the users' experience or attitudes when interacting with the chatbot. This model is a conceptual visual representation between constructs, organizing the

presumed relationships among concepts and addressing areas of study based on existing literature, and includes emergent ideas that have not been empirically validated or substantiated (Luft et al., 2022). However, the above model was not selected for this study for several reasons. The AICBCM is a conceptual model and has not been conceptually tested or validated. This dissertation also did not aim to evaluate the entire chatbot development pipeline or assess all user experience design interfaces. Hence, this dissertation proposed a separate integrated model.

To bridge the gaps in the current understanding within the “Evaluating Mechanisms” segment of the Artificial Intelligence Behavior Change Model, three theoretic frameworks will be considered: the Health Belief Model (HBM) offers predictors for health attributes, the Unified Theory of Technology Acceptance Model (UTAUT) contributes functional attributes from a usability perspective, and the Computer Are Social Actors (CASA) framework evaluates interactional attributes. By considering these three theories together, I hope to achieve a more comprehensive understanding of health chatbots and their potential to facilitate health and behavioral change in users.

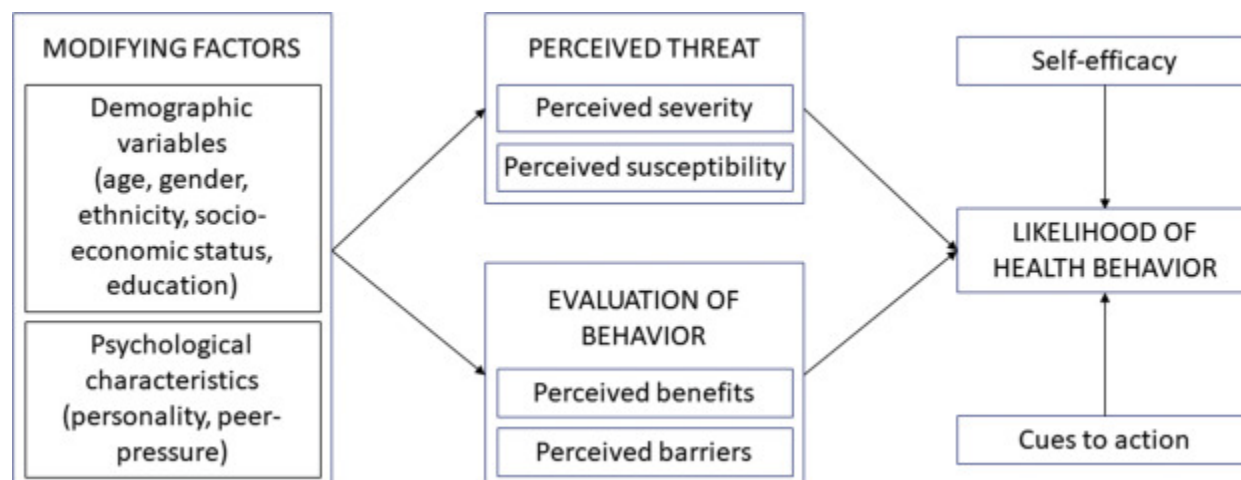
The Health Belief Model (Health Attributes)

Health attributes encompass factors of individual-related health beliefs and perceptions that would provide understanding and prediction of the likelihood of the individual engaging in health behavior. The Health Belief Model (HBM) is an established theoretical framework in health communication and psychology that seeks to understand and predict the likelihood of an individual engaging in health behaviors by examining individual health beliefs and perceptions (Champion & Skinner, 2008). The model was originally established in the 1950s by the US Public Health Department to understand the failure of a tuberculosis testing program (Bauer,

2004). The original health belief model, as seen in Figure 3 below, shows multiple predictors resulting in the likelihood of health behavior or outcome.

Figure 3

The Health Belief Model (Champion & Skinner, 2008).



The predictors of HBM include “Perceived Threat” and “Evaluation of Behavior,” and outcome variables include the “Likelihood of engaging in a Health Behavior” impacted by factors such as “Self-efficacy” and “Cues to Action.” In adapting HBM to evaluate intentions to use SRH chatbots for SRH management, the variables perceived severity and susceptibility were excluded. While central to traditional HBM, these variables focused on an individual’s belief on vulnerability of contracting a health condition and its subsequent consequences (Jones et al., 2015). However, one of the main objectives of this study is to investigate intentions to engage with SRH chatbots as a health management tool and not assessing individual’s beliefs about health risks and susceptibility. Removing these variables helps to bridge the gap in HMC literature by focusing on chatbot interactions rather than risk-oriented decisions. This also supports the second objective of examining how SRH chatbot interactions differ within the

LGBTQ+ subgroup who often face challenges accessing SRH resources. Focusing on other variables such as perceived benefits and barriers could generate more actionable insights that could inform the development of more inclusive SRH tools (Rajapakshe et al., 2024).

Perceived benefits, perceived barriers and self-efficacy were among the variables retained in this adapted model due to their strong theoretical and empirical relevance in predicting intentions to use an intervention (Huang & Gerend, 2024). Perceived benefits were critical in capturing users' evaluation of the chatbot's functionalities and informational utilities from the health perspective. Perceived barriers addressed users' concerns and hesitations accounting for psychosocial and attitudinal resistance that might not be fully addressed by usability related variables. Self-efficacy was an important indicator of engagement and sustained use.

Instead of focusing on risk appraisal, these variables explore the balance between facilitators and barriers when using SRH chatbots. Perceived benefits assess the value and worth of the SRH chatbot, perceived barriers identify the factors that could deter SRH chatbot usage and self-efficacy capture the user's confidence when navigating the SRH chatbot and if it would lead to engagement or subsequent underutilization of the resource. These three variables support the overarching goal of building a contextually relevant model to evaluate users' intentions to use SRH chatbots for SRH management. Table 1 provides the consolidated definition as well as examples for each of the constructs present in the HBM model.

Table 1

Health Belief Model Constructs

Construct	Definition	Example in Context
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Perceived Benefits	Refers to an individual's belief about the advantages of using a health tool to manage their SRH health.	When considering using an SRH chatbot, an individual might consider how it could provide an accessible judgement-free resource as compared to possible stigmatizing environments, encouraging increased intentions to engage with the SRH chatbot.
Perceived Barriers	Refers to an individual's belief about the challenges that could prevent the use of a health tool.	An individual might feel uncertain about disclosing their sensitive SRH information or question an SRH chatbot's ability to understand their unique needs accurately. This could reduce their intentions to engage with the SRH chatbot.
Self-Efficacy	Refers to an individual's confidence in their ability to use a health tool effectively.	As individuals interact with an SRH chatbot more frequently, they may develop more confidence in navigating the SRH chatbot leading to increased willingness to use this resource to manage their SRH.

Likelihood of Use	Refers to an individual's intention to use a health tool.	After learning about an SRH chatbot's features and capabilities, individuals may have stronger intentions to use the chatbot for their SRH management.
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HBM is used as one of the most important theoretical models to evaluate health behavior changes (Karl et al., 2022). It has proven to be a dependable framework for forecasting health-promoting behaviors across a range of health domains, including HPV prevention, COVID-19 prevention, and the prevention of sexually transmitted infections (Houlden et al., 2021; Lin et al., 2017; Li et al., 2019). While HBM has been used to evaluate some digital health products such as the use of wearable health products and stress apps and its subsequent effects of increasing healthy behavior (Ha et al., 2023; Paganin et al., 2023), it has not been widely used to assess health chatbots from an individual-level health perspective. There are even fewer studies that employ health-specific theoretical frameworks to comprehensively grasp users' attitudes and perceptions concerning SRH, identifying the possible impact this has on motivation to engage with SRH chatbots. This dissertation will look at the intentions to use SRH chatbots for SRH management.

Theoretical Model Limitations (HBM)

When employed to evaluate digital health interventions, HBM overlooks the integration of functional perspectives inherent to the digital product. Although health attitudes and perceptions play a crucial role in motivating behavioral change, it is imperative not to disregard the functionalities and features offered by digital products. When digital health innovators

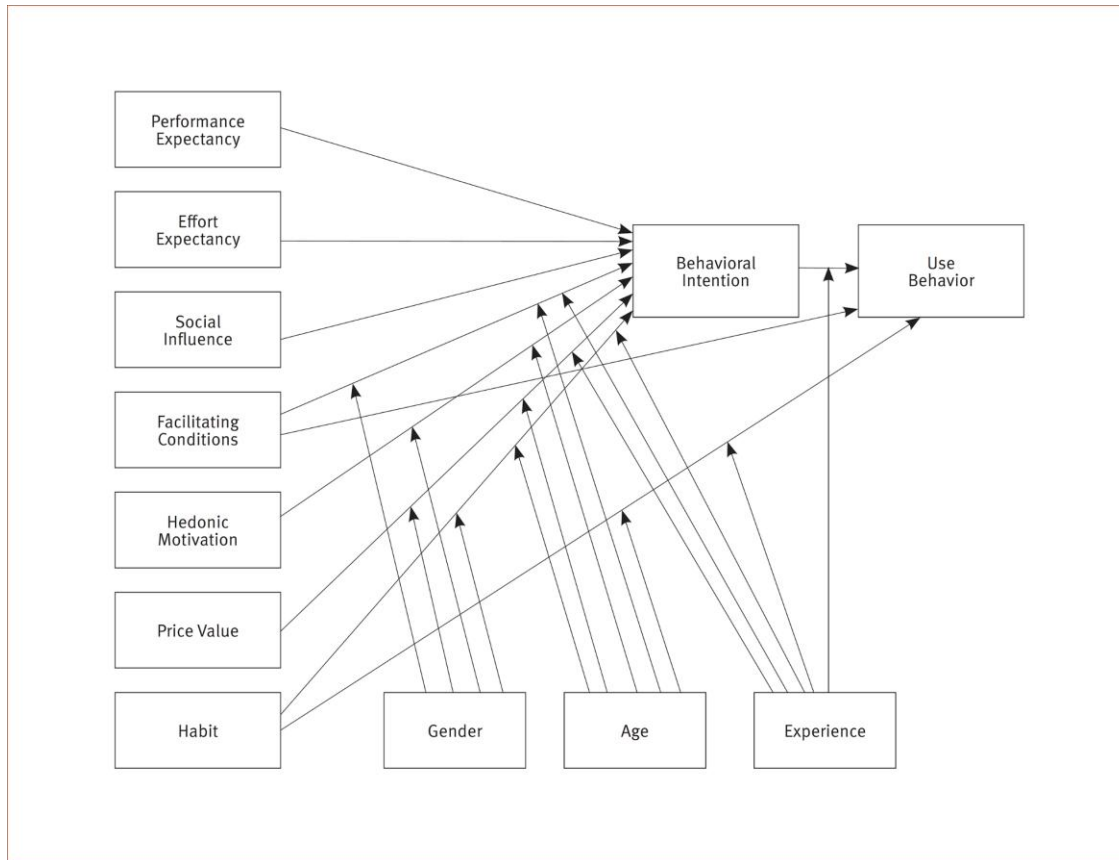
neglect the functionalities and features of digital products can undermine their effectiveness in promoting a behavior change (Senbekov et al., 2020). These aspects play a critical role in facilitating user engagement, providing relevant information, and delivering interventions in a user-friendly manner. By considering these functionalities alongside health perspectives, health researchers can optimize the user experience, enhance usability, and ultimately optimize the impact of digital health interventions to maximize positive health outcomes.

Unified Theory of Acceptance and Usage of Technology 2 Model (Functional Attributes)

Functional attributes focus on the usability and effectiveness of the chatbots in facilitating user interaction and achieving desired health outcomes. The Unified Theory of Acceptance and Usage of Technology (UTAUT) is a comprehensive model that was developed to understand and predict users' intentions to adopt and utilize various technological products. It is a combination of the Theory of Reasoned Action (Fishbein & Ajzen, 1975), the Theory of Planned Behavior (Ajzen, 1991), the Technology Acceptance Model (Davis, 1989), the Motivational Model (Davis et al., 1989), the Social Cognitive Theory (Compeau & Higgins, 1995), Model of Personal-Computer Utilization (Thompson et al., 1991), combined Technological Acceptance Model and Theory of Planned Behavior (Taylor & Todd, 1995) and Innovation Diffusion Theory (Moore & Benbasat, 1991). The UTAUT model, as seen in Figure 4, builds upon its predecessor by integrating additional key constructs from established theory.

Figure 4

The Unified Theory of Acceptance and Usage of Technology Model (Venkatesh et al., 2012).



UTAUT2 is an extension of the first UTAUT model offering a more comprehensive evaluation of consumer technology, including three new constructs (hedonic motivation, price value, and habit) (Venkatesh et al., 2012). With the inclusion of additional constructs, UTAUT2 has a higher predictive ability explaining about 74% of the variance in the users' behavior intentions and 52% of the variance in consumers' technology usage (Venkatesh et al., 2016). Table 2 consolidates the definition and examples in this context for each of the constructs in the UTAUT2 model. However, due to the exclusion of many UTAUT2 constructs, this study will follow the basic UTAUT model. Excluded constructs include price value as most SRH chatbots

are free and available for public use and habit is a construct that needs to be tested using a longitudinal experimental design. Facilitating conditions was removed as it represents the technical and organizational infrastructure of technology focusing on post-adoption usage rather than initial intentions to use the technological product (Venkatesh et al., 2012). Hedonic motivation was removed because it represents the degree to which the technology is perceived as enjoyable or fun to interact with. SRH chatbots are largely task-oriented acting as a digital navigator for SRH management, hence it is not characterized to be fun which would be misinterpreting the nature and purpose of the SRH chatbot.

Table 2

The Unified Theory of Acceptance and Usage of Technology (UTAUT) Constructs

Construct	Definition	Example in Context
Performance Expectancy	The degree to which an individual believes that using technology will help them to accomplish tasks more effectively or improve their performance.	An individual may believe that engaging with an SRH chatbot will help them access accurate and judgement-free SRH resources that could benefit their SRH.
Effort Expectancy	The degree of ease associated with using a technology.	An individual may be motivated to use a chatbot to manage their SRH as they find it intuitive and easy to use.

Social Influence	The degree to which an individual perceives that others (such as friends, family, or healthcare providers) believe they should use a particular technology.	If an individual's friend endorses using an SRH chatbot as a helpful resource, they may feel more motivated to use it based on that external encouragement or perceived social norm.
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Many past studies have explored health and medical digital products and services using the UTAUT and UTAUT2 model. For example, Schretzlmaier and colleagues (2022) used the UTAUT2 model to predict mHealth acceptance among diabetic patients. In the health chatbot domain, the UTAUT2 model has been used to evaluate HIV health chatbots identifying the factors hindering and promoting the acceptance of an AI chatbot aimed at aiding HIV testing and prevention among men who have sex with men (Peng et al., 2022). In another study, the UTAUT model was used to explore and assess the effectiveness, functionality, and user acceptance of a developed mental health chatbot intended for educating users and enhancing health literacy (Mokmin & Ibrahim, 2021). However, the UTAUT model has not been used to evaluate sexual health-specific chatbots widely.

Theoretical Model Limitations (UTAUT)

A key limitation of the UTAUT model is its lack of health-specific context (Schmitz et al., 2022). Initially developed to test the intentions to adopt technology in an office setting (Venkatesh et al., 2012), the model lacks health-specific constructs that could influence the intention to uptake digital health products. This would affect the testing of health products by

overlooking critical factors specific to health contexts that influence individuals' intentions to adopt digital health products. Considering these health-specific constructs is necessary for the model to accurately predict or explain individuals' willingness to use digital health products, leading to complete assessments and potentially ineffective interventions in health settings. Therefore, it is crucial to incorporate health-specific factors into the model to ensure its applicability and effectiveness in testing health products. (Davenport & Kalakota, 2019).

The Computers Are Social Actors Framework (Interactional Attributes)

Lastly, interactional attributes pertain to anthropomorphic cues, which can significantly impact user engagement and behavior change outcomes. The Computers Are Social Actors (CASA) framework stemmed from Reeves and Nass's (1996) media equation theory, arguing that when mediated representations mimic real-life interactions, humans tend to respond naturally and mindlessly (Reeves & Nass, 1996). The CASA framework has also been called the social responses to communication technologies (SRCT) approach (Sundar & Nass, 2000), focusing on how technologies are social actors applying humanistic characteristics when interacting with human users.

CASA is frequently used as a framework to direct research within various fields including human-machine communication (HMC), human-computer interaction (HCI), human-robot interaction (HRI), human-agent interaction (HAI), and media effects. These specialized areas, as well as the research conducted within CASA, have experienced significant growth over the last three decades, propelled by advancements in technology and the widespread integration of social technologies into domains such as healthcare, education, and domestic environments (Baylor, 2011; Fortunati, 2018; Kenny et al., 2008; Takayama, 2015). In efforts to extend the scholarship and include CASA's applicability to different technologies and human-machine

communication, Gambino and colleagues (2020) suggest emphasizing anthropomorphism as a key determinant in evaluating behavioral intentions to use digital products (Gambino et al., 2020).

Anthropomorphism refers to attributing human traits or qualities to an entity, indicating its potential for social interaction and communication (Waytz et al., 2010). Individuals may perceive human-like characteristics such as appearance, behaviors, or communication by a digital entity either in its form (form anthropomorphism) or actions (behavioral anthropomorphism (Nowak & Fox, 2018). Research within the CASA paradigm has generally indicated positive effects of anthropomorphism and subsequent intentions of digital product use (de Graaf & Allouch, 2013). Recent studies have investigated the impact of human-like traits in conversational agents on their acceptance across various domains, emphasizing anthropomorphism and its impact on human chatbot communication (de Graaf & Allouch, 2013)..

This aspect holds significance in research on SRH chatbots, where imbuing these chatbots with human-like traits aligns with users' favorable perceptions of them, potentially increasing their inclination to adopt them. Rahman and colleagues (2021) observed that there was an increase in enthusiasm when users engaged with the health chatbot, AdolescentBot, when the chatbot exchanged human-like pleasantries when communicating with the users (Rahman et al., 2021). In a separate study focusing on SnehAI, culturally appropriate social cues, and friendly and empathetic conversational styles appealed to users' engagement (Wang et al., 2022). Nadarzynski et al. (2021) noted that users' reluctance to use sexual health chatbots stemmed from the perception that the chatbots lacked emotions, greetings, and social dialogues. Furthermore,

some users reported that these chatbots appeared artificial and machine-like, contradicting their expectations of a naturalistic and familiar communication format.

From the communication perspective, empathetic communication in the form of chatbot response has proved to be effective in providing support and care for users, impacting chatbot use (de Gennaro et al., 2020). Empathetic chatbots provide emotional support through psychological safety and judgment-free interactions, especially important when communicating sensitive health issues (Pickard et al., 2016). An empathetic communication style can foster a trusting and emotional connection between users and the chatbot, likely increasing engagement because of familiarity and relatability. This has not been extensively integrated into theoretical frameworks aimed at assessing intentions to use SRH chatbots. Despite the growing prominence of chatbots in sexual health interventions, theoretical frameworks often overlook the interpersonal dynamics that underpin human chatbot interactions.

Table 3

The Computers Are Social Actors Framework (CASA) Construct Definitions and Examples

Construct	Definition	Example in Context
Human-Like Communication	The extent to which a chatbot uses language and interaction patterns that resemble those of a human.	An individual might be more inclined to engage with an SRH chatbot if it communicates like how a real human would instead of using robotic phrasing.
Perceived Warmth	The extent to which a chatbot is perceived as	An individual may be comfortable using an SRH chatbot if a welcoming tone is

	friendly and welcoming in tone and responses.	used to reduce anxiety when discussing sensitive health topics.
Perceived Empathy	The degree to which a chatbot acknowledges and validates the users' emotions.	A user may be more motivated to engage with an SRH chatbot if it recognizes the users' emotions and provides a judgement-free space.
Support for Autonomy	The extent to which a chatbot gives users the space to guide conversations rather than imposing a fixed flow.	A user may prefer using an SRH chatbot that lets them choose the topics or questions they want to explore, instead of following a rigid script.

Anthropomorphism, Performance Expectancy, and Effort Expectancy

Differing viewpoints exist regarding the impact of anthropomorphism on the usability or functional aspects of the chatbot. For instance, the Uncanny Valley Theory suggests that as robots or other non-human entities become more human-like in appearance and behavior, there is a point where they evoke a feeling of eeriness or discomfort in observers (Katsyri et al., 2015). This phenomenon could threaten a human's unique self-identity, affecting perceptions of the chatbot's ability (performance) and expectations of effort required to use the chatbot (effort) (Vitezic & Peric, 2021). Similarly, highly anthropomorphic AI-powered interventions may require additional operating effort aside from learning to use the device, users must also apply human-like social skills when interacting with the digital product (Vitezic & Peric, 2021).

Contrasting findings have shown that anthropomorphism is positively related to the usability aspects of digital products as users appreciate human-like competence when interacting with the application, promoting performance expectancy (Blut et al., 2021). Additionally, studies have found that human-like cues evoke a sense of norm and familiarity when users interact and communicate with digital applications, making it easier to use the application, positively relating to effort expectancy (Balakrishnan & Dwivedi, 2021). A study about the intentions to use sexual health chatbots by Liew and colleagues (2023) evaluated the relationship between anthropomorphism and performance and effort expectancy. Results showed that anthropomorphism had a positive relationship with performance expectancy, concluding that humanizing a chatbot leads to stronger perceptions that the chatbot can help to resolve the user's task (Liew et al., 2023). The authors further explained that the anthropomorphism characteristics of the chatbot could have subliminally prime users to attribute more competence to the chatbot's AI systems (Blut et al., 2021). However, the study did not find any significance between effort expectancy and anthropomorphism likely because of the nature of the chatbot used in the study. The chatbot used in the study had limited human-centric features from both the design and language programming perspectives, lacking communication intelligence and empathetic responses that could have made it more challenging for human-chatbot interaction (Nadarzynski et al., 2021).

Digital Health Literacy

At the heart of this convergence lies the concept of digital literacy, a pivotal component of digital determinants of health, shaping individuals' abilities to engage with digital tools and platforms effectively (van Kessel et al., 2022). Digital health literacy has also been labeled as the “super social determinant of health” indicating its implications and impact in shaping

individuals' intentions to use digital health interventions and ultimately influencing overall health outcomes (Sieck et al., 2021). Digital health literacy is “the ability to use information and communication technologies to find, evaluate, create, and communicate information, requiring both cognitive and technical skills” (American Library Association, 2017; UNESCO, 2011).

Another study added that digital health literacy was a factor that had an impact on how digital health information affected an individual's overall behavior and ability to prepare for health challenges (Stoumpos et al., 2023). Fundamentally, digital health literacy is a universally recognized key construct that can ensure the equitable distribution of digital health interventions (Campanozzi et al., 2023).

While digital health literacy emerges as a cornerstone of digital determinants of health, impacting the intentions to interact with health-related technologies, it has not been tested widely as a moderator against self-efficacy in this context. Testing this construct as a moderator will allow for a deeper understanding of how it affects the direction and strength of the relationship between predictors and intentions of chatbot use (van Kessel et al., 2022). Uncovering digital health literacy also helps to elucidate how confidence through education and awareness could exert influence on individuals' willingness to engage with chatbots for health-related purposes. Considering digital literacy as a moderating variable in this integrated theoretical approach can provide valuable insights into the interplay between digital competencies, user perceptions, and behavioral intentions within the realm of digital health. This approach contributes to a more comprehensive understanding of the factors shaping individuals' adoption and utilization of innovative digital health technologies like chatbots.

Behavior Intention

The relationship between behavior intentions, particularly through the utilization of SRH chatbots, and the likelihood of better SRH management is crucial in promoting informed decision-making and risk reduction strategies among the young adults' populations (Zou et al., 2024). Chatbots, as innovative digital health interventions, offer accessible, confidential, and stigma-free avenues for individuals to seek sexual health information and support, thereby facilitating the likelihood of adoption (Haque et al., 2023). Past studies have shown that by engaging with chatbots, individuals can clarify misconceptions, receive personalized advice, and access resources to enhance their understanding of safe sexual practices, ultimately shaping their intentions to adopt preventive behaviors (Zhang et al., 2020; Peng et al., 2022; Mills et al., 2023). Heightened behavior intentions facilitated by chatbot interactions are strongly linked to an increased likelihood of developing safe sexual health practices, such as consistent condom use, regular STI testing, and communication with partners about sexual health concerns (Nadarzynski et al., 2023). This underscores the potential of digital health interventions to empower individuals to make informed decisions and foster positive SRH outcomes.

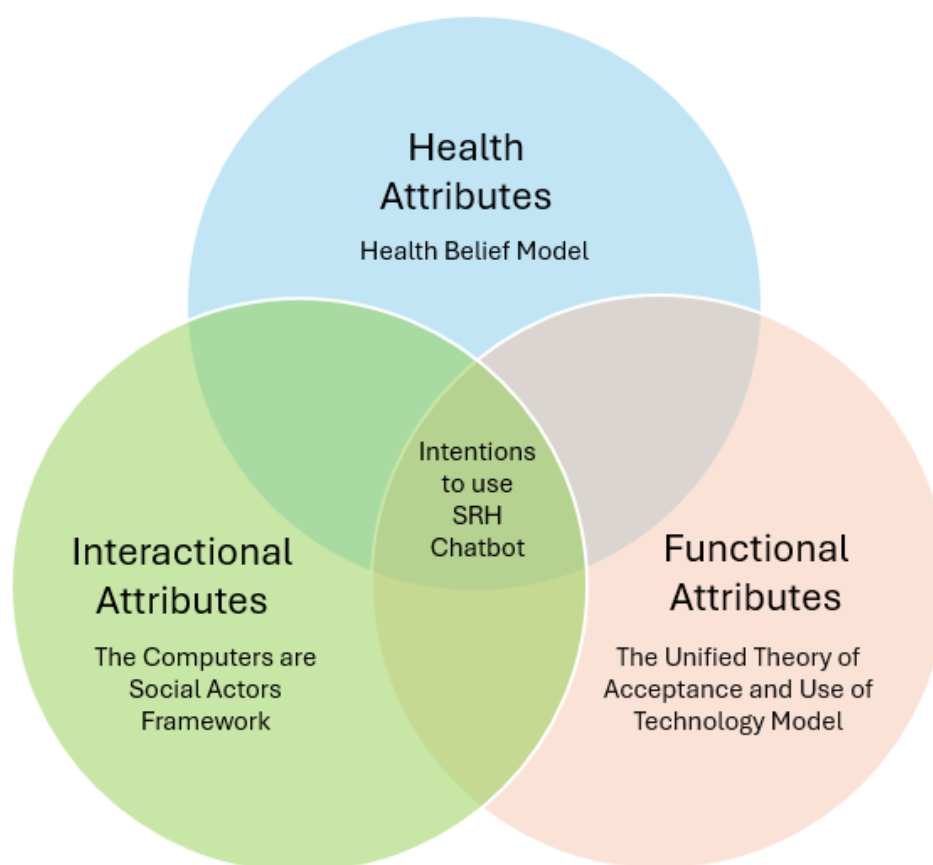
Proposing an Integrated Theoretical Approach

While both the Health Belief Model (HBM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) include behavioral intentions as outcomes, they individually lack specific constructs essential for a thorough evaluation of digital health products such as sexual health chatbots. However, each model offers unique constructs that are absent from the other, implying that their combination could provide a more comprehensive framework for assessing and understanding the adoption of such health technologies. Furthermore, understanding the mechanisms of interactional attributes using the CASA framework can help to enhance the

design and implementation of chatbots, leading to increased engagement and overall adoption of the chatbot. Figure 5 shows a visual representation of the integrated theoretical approach, divided into three respective attributional categories, for this study.

Figure 5

Visual Representation of Integrated Theoretical Approach.



Note. The integrated approach uses theoretical perspectives combining health attributes, functional attributes, and interactional attributes to provide a comprehensive framework for understanding and assessing chatbots for health and behavioral change.

This dissertation endeavors to understand the dynamics of SRH chatbot engagement, and its potential to enhance SRH management. It aims to identify how SRH chatbot interactions can contribute to the advancement of health-related knowledge, attitudes, and behaviors in the realm of SRH. Following a mixed methodology, the first study included a quantitative national survey to identify if the proposed integrated model was valid and identified the factors that contributed to intentions to use SRH chatbots. The second study was a qualitative study that incorporated co-creation techniques to examine self-disclosure and chatbot message design. The next chapter will provide a detailed exposition of the studies, outlining their methodologies in alignment with the research objectives.

CHAPTER 4

Methods

This chapter focuses on the methodology used to conduct the quantitative and qualitative studies in this dissertation. A mixed methods approach was employed, with findings from the quantitative survey guiding the subsequent steps of the qualitative component. This approach was chosen to capture both the breadth and depth of user experiences with AI-powered chatbots for SRH. While quantitative methods allowed for the identification of generalizable patterns and predictors of chatbot engagement, qualitative methods offered deeper insight into the interpretive and contextual nuances behind those patterns—such as how users perceived message design and relational cues.

Research methodologies in HMC is unique as they offer a blend of traditional communication theories with interdisciplinary approaches to understand the nature of interaction between humans and machines (Greussing et al, 2022). Communication between humans and machines is no longer linear processes and includes the interactive exchange of messages where machines or social robots are also active participants in the communication process (Greussing et al., 2022). Hence, there is a growing need to study the emerging communicative relationships between humans and machines from a methodological perspective (Gibbs et al., 2021). The primary objective of HMC is to understand the nature of why and how humans interact with communicative agents (Guzman & Lewis, 2020). This includes examining how humans perceive technology, factors that enable or challenge their use of technology and the interactional and reciprocal relationships between humans and machines (Etzrodt & Engesser, 2021; Richards et al., 2022).

Testing communicative agents such as chatbots in empirical studies has posed several challenges as there are few validated scales developed uniquely for measuring interactions between human and machines (Kim & Sundar, 2012). Existing measurement scales often examine either human communication or technology use in isolation. This siloed approach limits their ability to capture the complexity of interactions that occur in Human-Machine Communication (HMC) contexts. In response, recent scholarship has emphasized the need for multidimensional scales that integrate both communicative and technological perspectives (Weidmüller, 2022). This shift aligns with the objectives of the present dissertation, which aims to understand how users engage with AI-powered chatbots as relational and informational partners. To support this goal, Roo, a sexual health chatbot, was selected as the stimulus because it exemplifies the dual role of chatbots in HMC—delivering information while also simulating interpersonal communication. Roo provided a suitable platform to evaluate user perceptions of both message design and social presence within a health-specific chatbot interaction. The studies in this dissertation will be anchored around Roo.

Conducting studies with publicly available agents are effective, cost efficient, and less prone to errors as these agents have developed underlying mechanisms (Greussing et al., 2022). Hence, SRH chatbot Roo was used in this dissertation. Roo is an SRH chatbot launched in 2019 by Planned Parenthood, a nonprofit organization that provides sexual education and sexual healthcare in the United States (Planned Parenthood, 2019a). While Planned Parenthood initially designed Roo for adolescents and young adults, they have since expanded their reach as a resource to anyone who needs to clarify doubts or has questions about SRH (Planned Parenthood, 2019b). The organization also stated that they wanted to create an AI driven source

where users could receive judgment-free, inclusive, and scientifically accurate sexual health advice.

Quantitative Study

The quantitative study examined an integrated theoretical approach that combined the Health Belief Model (HBM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Computers Are Social Actors (CASA) paradigm. By employing Partial Least Square-Structural Equation Modeling (PLS-SEM), this study evaluated the model fit and explored the relationships among variables to uncover predictors of motivations to show individuals' intentions to use an SRH chatbot to manage their health. Statistical software SmartPLS 4, which is designed for estimating complex path models, was used for statistical analysis in this dissertation. PLS-SEM was chosen for its exploratory abilities and robustness in modeling complex relationships between multiple constructs (Riou et al., 2016). The proposed integrated model was specified in SmartPLS 4, and the measurement model was first evaluated to identify internal consistency reliability, convergent validity and discriminant validity to ensure constructs reflected their intended purpose accurately (Hair & Alamer, 2022). Following that, the structural model was assessed to evaluate the hypothesized relationships between constructs. Path coefficients and t-values were calculated, the amount of variance was examined, and effect sizes were evaluated to gauge the significance of each predictor (Hair & Alamer, 2022).

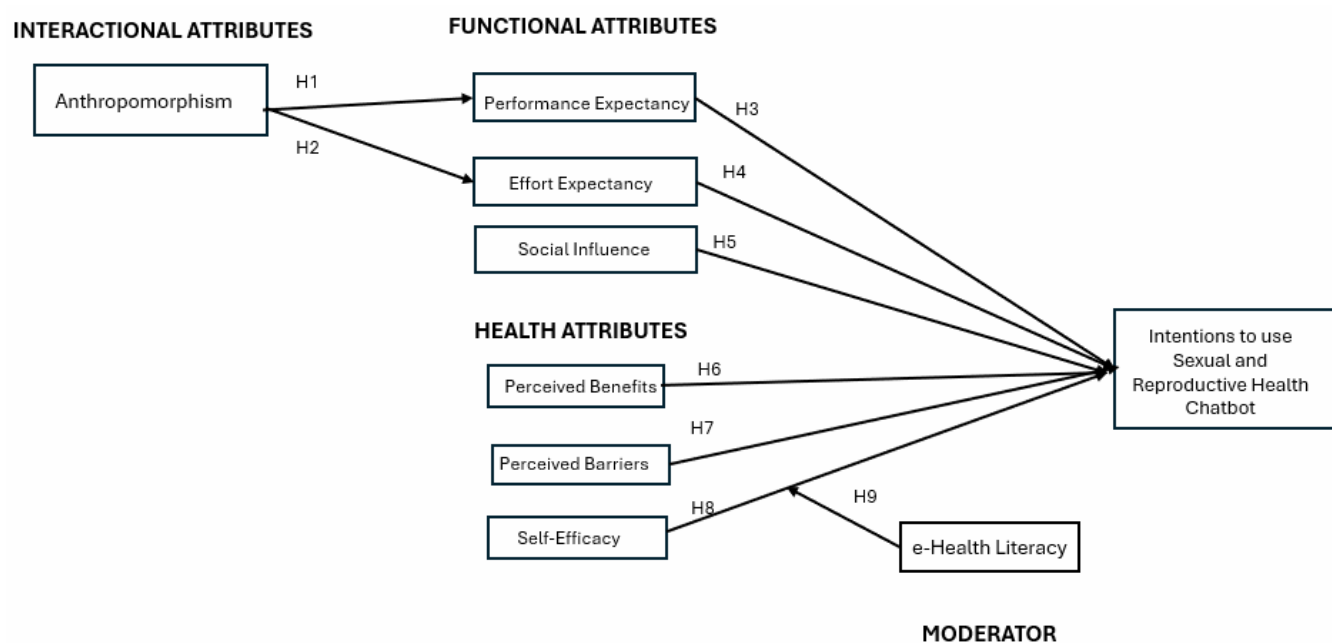
Upon noting that the measurement model was valid, a subgroup analysis among LGBTQ+ participants was also conducted to assess the structural model and how the relationships between the constructs and the outcome variable differed compared to the general population. This analysis contributed to the growing but underexplored literature on HMC

interaction in health communication, specifically understanding different dimensions that act as motivators or barriers to using technology for healthcare.

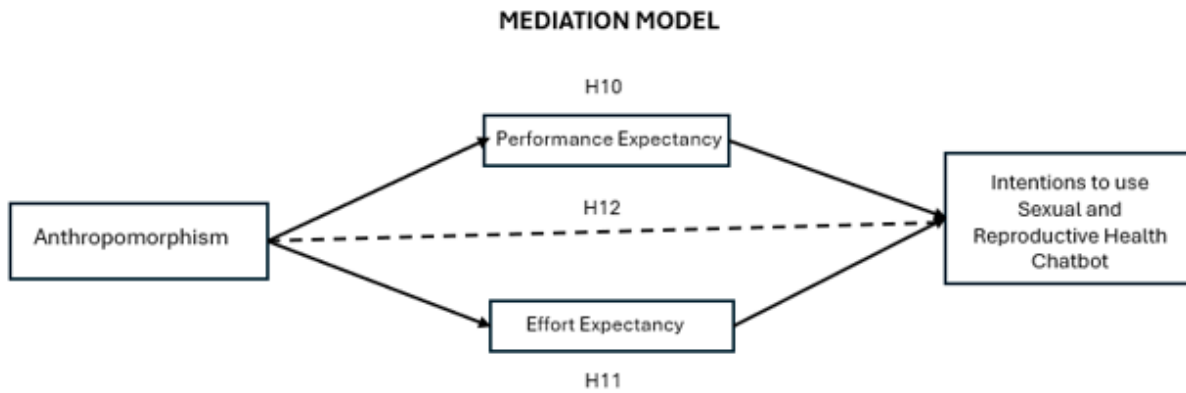
Figure 6 iterates the proposed conceptual integrated model alongside the research questions and hypotheses.

Figure 6

Proposed Integrated Model



Proposed Mediation Model



Research Questions

RQ 1: To what extent does the proposed integrated theoretical framework account for intentions to use the sexual and reproductive health chatbot to manage SRH?

RQ2: Does the structural model for intentions to use an SRH chatbot differ for LGBTQ+ individuals in the context of SRH management?

Hypotheses

H1: Anthropomorphism is positively related to performance expectancy.

H2: Anthropomorphism is positively related to effort expectancy.

H3: Performance expectancy is positively related to intentions to use a sexual and reproductive health chatbot.

H4: Effort expectancy is positively related to intentions to use a sexual and reproductive health chatbot.

H5: Social influence is positively related to intentions to use a sexual and reproductive health chatbot.

H6: Perceived benefits are positively related to intentions to use a sexual and reproductive health chatbot.

H7: Perceived barriers are negatively related to intentions to use a sexual and reproductive health chatbot.

H8: Self-efficacy is positively related to intentions to use a sexual and reproductive health chatbot.

H9: e-Health literacy moderates self-efficacy with behavioral intentions.

H10: Performance expectancy mediates the relationship between anthropomorphism and the intention to use a sexual and reproductive health chatbot.

H11: Effort expectancy mediates the relationship between anthropomorphism and the intention to use a sexual and reproductive health chatbot.

H12: Anthropomorphism is positively related to intentions to use a sexual and reproductive health chatbot.

Recruitment and Data Collection

In partnership with the Planned Parenthood Federation of America (PPFA) and upon receiving approval from the Institutional Review Board at the University of Georgia, 1,200 participants from across the United States were recruited for this study using the platform UserZoom. UserZoom is a data collection tool under the overarching UserTesting website. It allows researchers to test digital products and understand how users interact with these products by conducting large-scale surveys and usability testing (Koundinya et al., 2017). Participants (18-32 years) were recruited directly on the UserZoom platform with a national representation across all racial, ethnic, and sexual orientation demographics in the US. While the CDC reported that 50.5% of SRH issues were among 18-24 years old Americans (CDC, 2023), this study

expanded the upper age limit to 32 years old as the 25-32 age range represented a transitional life stage marking changes in healthcare access, evolving relationships and increased digital health engagement (Eliason et al., 2015). To be included in this study, participants had to fall between the 18-32 age range, have access to technology, interacted with Roo, and answered the attention check question accurately (What is the name of the chatbot you interacted with?) and resided in the US to have access to the testing platform. Participants who failed these criteria were excluded from the study.

Procedure

Participants first signed an informed consent and proceeded to the screening survey. The screening survey included questions to ensure that participants were between 18 and 32 years old and followed the instructions provided to interact with the chatbot before moving to the main survey. Figure 7 shows the instructions for participants to visit a link guiding them to explore chatbot Roo. The unique link offered the standard functionalities of the chatbot while enabling enhanced tracking to determine whether participants accessed the link. This level of tracking would not have been possible with a generic public link. Following that, participants were provided with instructions and search questions specifically about SRH on the chatbot.

Figure 7

Instructions for Chatbot Interaction

*13. Please take a moment to read the following instructions before proceeding to the next part of the survey:

Instructions

Before proceeding to the main portion of our survey, please follow these steps to use the chatbot:

1. Visit the following Website:

- Click on the following link to access the chatbot:
 - <https://roo.plannedparenthood.org/jun24test>

2. Explore the Chatbot (5 - 10 minutes):

- Interact with the chatbot by asking questions or exploring the available topics related to sexual and reproductive health.
- Here are some ways you can interact with the chatbot:
- Ask Questions/Explore Topics/Seek Advice:
 - "What are the common symptoms of a urinary tract infection?"
 - Click on topics like "Birth Control Options" to learn about different methods available.
 - Check out "Sexually Transmitted Infections (STIs)" to understand prevention and treatment.

3. Return to the Survey:

- Once you have finished exploring the chatbot, return to this survey to continue with the next set of questions.

Thank you for your participation!

Note. Participants were informed to interact and explore the chatbot before proceeding to the main survey.

Once completed, participants were informed to return to the screener survey to answer the attention check question. The attention check question asked participants to name the chatbot they had interacted with. Only participants who answered the questions correctly and had interacted with the unique chatbot link were given access to the main survey. The main survey included the key variables from the integrated theories. Participants took an average of 8.5 minutes to complete the survey. Once completed, all participants were thanked for their time and compensated with \$12 gift cards on the UserZoom platform. The data for the following study

was conducted in June 2023. The following chapter will include the results from the demographic data as well as measurement items used.

Qualitative Study

The other objective for this dissertation was to understand HMC from the qualitative lens, focusing on message design, the use of empathy and emojis and their impact on self-disclosure. Nadarzynski and colleagues developed the equitable health chatbot implementation roadmap, which provided specific recommendations to increase AI equity in digital health products (Nadarzynski et al., 2024). A key aspect of this roadmap was the co-designing and co-development phase when identifying features to improve and implement in chatbots (Nadarzynski et al., 2024). From the start, diversity and collaboration were strongly encouraged and the involvement of stakeholders and community partners from diverse communities were important to ensure that the recommendations from the message design or features perspective were user-centered and culturally sensitive (Nadarzynski et al., 2024). This phase laid the foundations for co-designing and improving the chatbot and was adapted to this dissertation.

The qualitative study was conducted in two phases. A co-designing session was initially conducted with partners from PPFA to identify contexts and co-create empathetic and non-empathetic chatbot messages. This was conducted in July 2023. This phase was informed by the principles of participatory design (Bonacin et al., 2019) and Nadarzynski's ethical AI development roadmap (Nadarzynski et al., 2024). Co-designing is a participatory research method that includes sharing power over the research process and development of products (Zogas et al., 2024). The philosophy of the co-designing process is to meaningfully involve the community to develop the product together (Albert et al., 2023). A key aspect of the co-

designing principle is to ensure that all participants involved have agency and ownership in the development process, knowledge is respected and valued and there is reciprocity and mutual exchange of information (Zogas et al., 2024). Another aspect of this process that was used included synchronous workshopping sessions to create the message designs using virtual platform Figma to design prototypes (Zogas et al., 2024). This allowed for rapid prototyping and an iterative feedback loop for any changes.

The second phase involved qualitatively examining the proposed messages through an open-ended survey and soliciting feedback about the messages. This was done to evaluate the preferences of the message type and how it impacted one's intentions to use the chatbot. An open-ended qualitative survey was chosen as it suited the exploratory nature of this study and allowed for a holistic and comprehensive understanding of message preferences (Albudaiwi, 2017). Open-ended survey questions provided a space for the respondents to share more opinions and use language that accurately represents their thoughts, shaped by their personal lived experience (Albudaiwi, 2017). In sensitive contexts such as those around SRH interventions, open-ended surveys allow for more expressive opinion sharing which might not be discussed in an in-person interview setting. This creates a heightened sense of individuality and uniqueness in expression (Albudaiwi, 2017). This was conducted in August 2023.

To analyze the data collected, thematic analysis was used to organize and examine the findings, understanding patterns within participants' feedback. Thematic analysis is a qualitative methodology used for identifying, analyzing and reporting themes or patterns within a data set (Braun & Clark, 2006). A step-by-step guide recommended by Braun and Clark (2006) was followed, starting with the familiarization of data noting initial ideas, generating initial codes, identifying appropriate themes, reviewing themes, defining and naming themes and finally

producing the final report or results of analysis (Braun & Clark, 2006). Using thematic analysis offered multiple advantages including flexibility and the suitability for participatory research where participants are involved as collaborators, aligning closely with the nature of this study (Braun & Clark, 2006). Furthermore, it allowed for the generation of unanticipated data and was useful in informing analysis that could be used for policy or intervention development (Braun & Clark, 2006).

Research Questions:

RQ1: How do empathetic versus non-empathetic communication styles in chatbot influence users' intentions to self-disclose and engage with a sexual and reproductive health chatbot?

RQ2: What are users' perceptions of human-like communication styles simulated by the chatbot, and how do these perceptions shape their decision to engage with a sexual and reproductive health chatbot?

RQ3: How do personalized responses enhance user satisfaction and intentions to use a sexual and reproductive health chatbot?

RQ4: What insights can be drawn from user feedback regarding the effectiveness of empathetic and non-empathetic messages in fostering trust and increasing intentions to use a sexual and reproductive health chatbot?

Procedure

Phase 1- Message Design Workshop

The first stage of this study was to investigate the type of empathetic and non-empathetic messages to create for the prototype. This involved a co-creation workshop where key stakeholders from Planned Parenthood's digital product team and research teams collaborated in a brainstorming session to develop empathetic and non-empathetic message content.

Participants and Recruitment

Digital health professionals (N=2), a product designer (N=1) and active researchers (N=2) on the digital products teams (Total participants=5) were invited to participate in this co-creation session. The participants were invited to join a one-hour brainstorming and message creation session via zoom.

Co-creation Workshop

The hour-long workshop discussed how empathetic and non-empathetic messages would look like. The findings revealed that some participants felt comfortable sharing personal information when empathy was integrated into chatbot interactions. However, some participants perceived overly empathetic chatbots as intrusive, expressing a preference for a clear both-human distinction to protect their privacy. Many viewed chatbots as supportive guides or information providers, with emotional support seekers favoring empathetic communication, while others preferred concise and factual responses. A balanced communication approach combining empathy with conciseness emerged as the preferred style for addressing sensitive topics and increasing self-disclosure. Empathetic language and the use of emojis enhanced comfort for some users, and real-time feedback highlighted a preference for empathetic over direct communication styles in certain contexts, underscoring the nuanced role of empathy in promoting self-disclosure while addressing privacy concerns. Following the presentation, the team utilized Figma to brainstorm and visualize potential designs for the chatbot responses, as illustrated in Figure 8.

Figure 8*Figma Brainstorming Session*

Empathetic and Inclusive Responses

- Recommendation: Ensure that chatbot responses are empathetic, inclusive, and use non-gendered terminology.
- Reason: 34% of participants want empathy and understanding in responses.
- Visual: Example of a chatbot response showing empathy and inclusive language.

Examples

1. Baseline Style: Traditional/Standard/ no much empathetic or emotional cues/content. Lots of explanations - Explainable AI (XAI)?
Eg: "Please tell me the main symptom that bothers you most"

2. Empathetic Style: Provide more emotional support/human like features, users desired greetings, friendly addresses, caring language, and potential treatment suggestions (i.e., what users should do to treat their symptoms, e.g., how to ease the symptoms and whether to see a doctor).

Empathetic conversation design

- Onboarding:** Warm and engaging, welcome, friendly, and helpful. Explain the purpose and benefits of the service.
- Disclosure:** Be transparent about data collection and usage. Be transparent about the limitations of the service.
- Error:** Offer clear guidance on how to resolve the issue. Offer clear guidance on how to contact support.

(a) Explanations for questions

(b) Explanations for diagnostic results

(c) Greetings

(d) Caring words

(e) Suggestions

3. Combine empathetic and explanation style. Would need help designing a combination style chatbot communication, example is basically a combination of both examples 1 and 2.

Based on these findings, the 5 participants in this workshop identified six key themes after several rounds of open discussions, to define the structure of an ideal empathetic conversation, which will serve as a foundation for guiding the message design process. In contrast, the non-empathetic message style was conceptualized as the inverse of these themes.

Each theme was accompanied by an example to illustrate how a potential message would be crafted. Table 4 below consolidates the six key themes for an ideal empathetic message design.

Figures 9 and 10 show the example of non-empathetic and empathetic message design.

Table 4

Themes for Empathetic Message Design

Theme	Description	Example
Warm and Friendly Greeting	Start with a welcoming tone to create a positive and approachable interaction.	"Hi there! 😊 I'm Chat, your guide for any questions you might have about sexual health. How can I support you today?"
Acknowledging with Affirmation	Use supportive phrases to validate the user's inquiry and demonstrate understanding.	"Absolutely! I'm glad you're learning about birth control options—it's a big decision."
Clear, Factual Information	Transition to providing straightforward, accurate, and evidence-based responses.	"There are several birth control options. Hormonal methods, like the pill, have different effectiveness rates."
Offering Further Assistance	Gently invite users to ask for additional information or clarification.	"If you'd like more details on any method, just let me know. I'm here to help."
Responding with Assurance	Use reassuring language to address sensitive topics and alleviate concerns.	"The pill is about 91% effective. There are risks like blood clots, especially for smokers."
Concluding Positively	End by reaffirming availability for support without adding pressure.	"I'm here anytime you have more questions. Take your time to find what's right for you!"

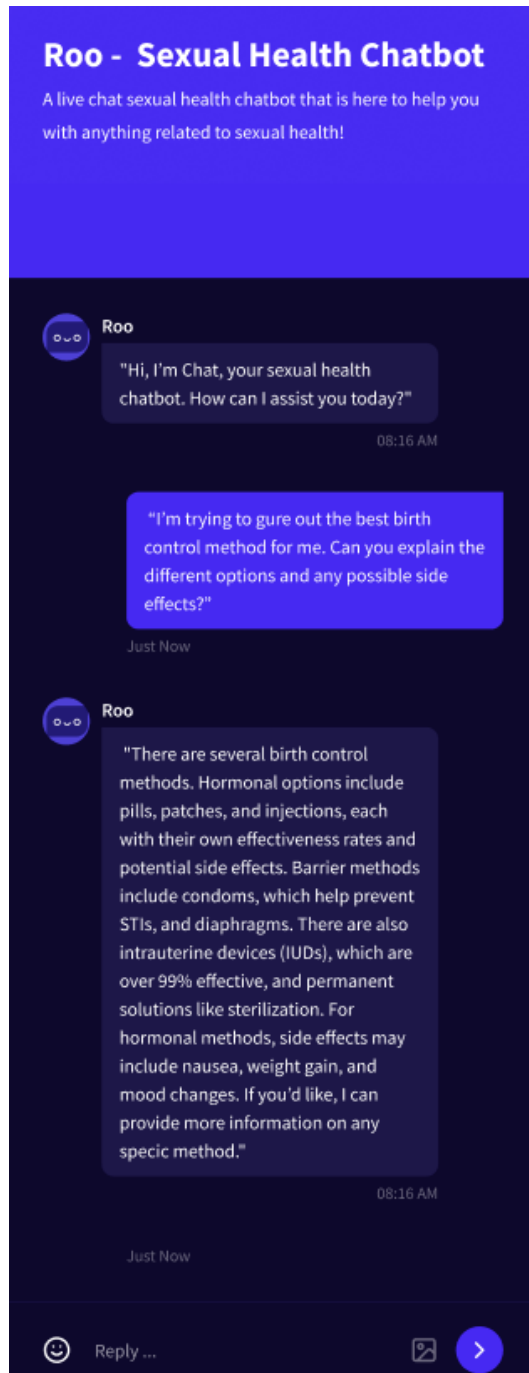
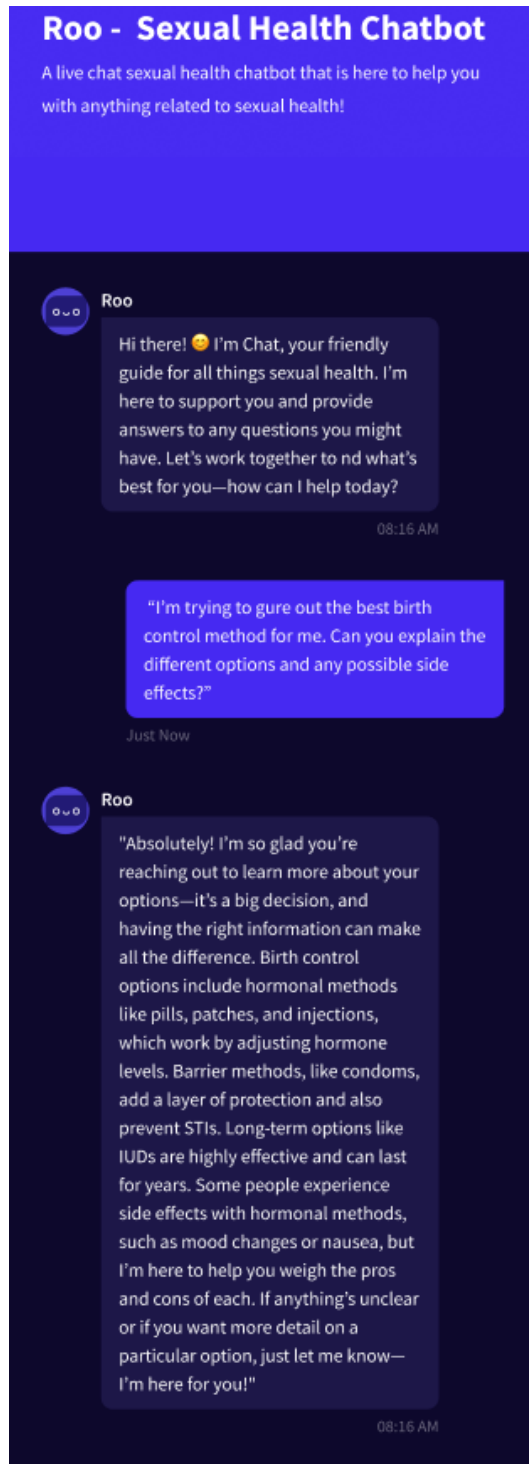
Figure 9*Non-Empathetic Message Design 1*

Figure 10*Empathetic Message Design 2*

Phase 2: Open-Ended Survey

Upon designing the chatbot messages, 20 college students from a research methods class were recruited to assess the messages and answer open-ended questions based on the self-disclosure theory (Archer & Burleson, 1980). The self-disclosure theory implies that when an individual reveals personal information, the beneficial nature of self-disclosure is amplified when the respondent shows support and validation often through empathetic messages (Ho et al., 2018). Similarly, as chatbots can facilitate comparable conversations, it is crucial to understand how users respond to these anthropomorphic messages and determine whether they help bridge the psychological gap in self-disclosure, ultimately enhancing intentions to use chatbots for managing health. Upon completing the survey, participants were given an extra credit point for their course. Survey questions can be found in Appendix A.

CHAPTER 5

Results

Quantitative Study of General Population

Measurement Items and Reliability Check

All measurement items were measured using a 7-point scale ranging from 1 (strongly disagree) to 7 (strongly agree). These items were adapted from prior established scales. The reliability check was evaluated using Cronbach's alpha coefficient. These analyses were performed using Statistical Package for the Social Sciences (SPSS) version 28.0 software. The measurement items and reliability check table found in Appendix C shows the outcome of the reliability check. The instrument used fulfilled the proposed criteria and was reliable.

Measurement Model

SmartPLS 4.0 was used to assess the measurement and structural model. This statistical software helped to analyze the psychometric properties of the measurement model and estimated the parameters of the structural model. The following section presents the results for the analysis to evaluate the validity and reliability of the measurement model.

Factor Loadings

Factor loadings are when each correlation matrix item correlates with the principal component. Factor loadings can range from -1.960 to +1.960, with higher values indicating a higher correlation of the item with the underlying factor (Tavakol & Wetzel 2020). All the items

in this study had a factor loading above the recommended .500 value for exploratory studies (Hair et al., 2016). Factor loadings are presented in Appendix D.

Indicator Multicollinearity

Variance Inflation Factor (VIF) is used to access multicollinearity when testing constructs or indicators in a study (Kim, 2019). According to Hair and colleagues (2022), multicollinearity does not occur when the VIF value is less than 5. Appendix E shows the VIF values for the indicators in this study. All the indicators have VIF values below the recommended threshold, hence there are no multicollinearity issues.

Reliability Analysis-Cronbach's alpha and Composite reliability

Reliability analysis is conducted to examine the degree to which measure an instrument is stable, consistent, and can be repeated (Kimberlin & Winterstein, 2008). In other words, when this instrument is administered on a separate occasion, it should yield similar or the same results. To establish reliability, this study examined Cronbach's alpha and the Composite Reliability (CR) presented in Table 5. Cronbach's alpha ranged from 0.738 to 0.932 and the CR ranged from .824 to 1.000 meeting the acceptable threshold of .700 and above (Hair et al., 2022) establishing construct reliability.

Table 5

Construct Reliability Analysis (Cronbach's Alpha and Composite Reliability)

	Cronbach's alpha	Composite reliability (rho_a)
Anthro	0.887	0.890
Barrier	0.738	1.000
Benefit	0.869	0.874
Efficacy	0.849	0.854

Effort	0.918	0.919
Intention	0.901	0.904
Perf	0.800	0.824
Social	0.853	0.860
e-Lit	0.932	0.934

Convergent Validity- Average Variance Extracted

Convergent validity is established when two or more measures intended to assess the same construct exhibit strong covariance, demonstrating that they effectively represent the underlying concept (Bagozzi & Phillips, 1991). According to Fornell and Larcker (1981), convergent validity is achieved when the Average Variance Extracted (AVE) for a construct is 0.50 or higher, indicating that the items sufficiently converge to measure the construct. In this study, all constructs achieved convergent validity, with AVE values ranging from 0.554 to 0.859.

Table 6

Construct Convergent Validity (AVE)

	Average variance extracted (AVE)
Anthro	0.748
Barrier	0.554
Benefit	0.792
Efficacy	0.769
Effort	0.859
Intention	0.834

Perf	0.719
Social	0.774
e-Lit	0.711

Discriminant Validity-Fornell and Larcker Criterion

The Fornell and Larcker criterion assesses discriminant validity by comparing the square root of the Average Variance Extracted (AVE) for each construct with its correlations with other constructs. Discriminant validity is established when the square root of AVE exceeds all inter-construct correlations (Fornell & Larcker, 1981). In this study, each diagonal value was greater than all off-diagonal values in the corresponding row and column shown in Table 7. Thereby providing strong evidence of discriminant validity.

Table 7

Discriminant Validity-Fornell & Larcker Criterion

	Anthro	Barrier	Benefit	Efficacy	Effort	Intention	Perf	Social	e-Lit
Anthro	0.865								
Barrier	0.070	0.744							
Benefit	0.690	0.156	0.890						
Efficacy	0.745	0.116	0.758	0.877					
Effort	0.696	-0.072	0.601	0.672	0.927				
Intention	0.624	0.192	0.681	0.790	0.481	0.913			
Perf	0.723	0.065	0.748	0.785	0.646	0.652	0.848		
Social	0.616	0.256	0.626	0.650	0.491	0.589	0.664	0.880	
e-Lit	0.700	0.056	0.631	0.734	0.735	0.610	0.676	0.545	0.843

Discriminant Validity-Cross Loadings

Cross loadings involve examining how strongly each measurement item correlates with its own constructs in comparison to other constructs. Table 8 shows that the individual indicators load more strongly on their own construct than on any other constructs, demonstrating that it is a good measure of its intended construct.

Table 8

Discriminant Validity-Cross Loadings

	Anthro	Barrier	Benefit	Efficacy	Effort	Intention	Perf	Social	e-Lit	e-Lit x Efficacy
Barrier_1	0.126	0.947	0.215	0.157	0.028	0.213	0.109	0.288	0.142	-0.057
Barrier_2	-0.063	0.582	-0.030	-0.050	-0.213	0.038	-0.062	0.052	-0.152	-0.030
Barrier_3	-0.096	0.653	-0.058	-0.014	-0.276	0.061	-0.061	0.067	-0.158	0.009
Benefit_1	0.592	0.144	0.887	0.703	0.508	0.660	0.667	0.548	0.583	-0.166
Benefit_2	0.658	0.097	0.896	0.670	0.601	0.554	0.690	0.565	0.570	-0.176
Benefit_3	0.597	0.171	0.887	0.647	0.503	0.593	0.641	0.560	0.529	-0.164
Efficacy_1	0.641	0.085	0.693	0.893	0.606	0.730	0.713	0.570	0.607	-0.188
Efficacy_2	0.658	0.150	0.688	0.911	0.592	0.706	0.708	0.577	0.609	-0.181
Efficacy_3	0.665	0.068	0.608	0.824	0.569	0.637	0.640	0.564	0.728	-0.254
Effort_1	0.663	-0.052	0.586	0.655	0.922	0.473	0.621	0.470	0.690	-0.312
Effort_2	0.627	-0.088	0.541	0.603	0.935	0.425	0.602	0.449	0.674	-0.331
Effort_3	0.642	-0.062	0.542	0.608	0.923	0.439	0.572	0.444	0.678	-0.353
Human_1	0.802	0.128	0.573	0.674	0.496	0.607	0.631	0.519	0.574	-0.174
Human_2	0.909	0.043	0.638	0.683	0.632	0.574	0.666	0.564	0.629	-0.240
Human_3	0.892	0.015	0.603	0.637	0.627	0.526	0.613	0.546	0.612	-0.251
Human_4	0.851	0.065	0.570	0.588	0.643	0.458	0.591	0.501	0.604	-0.268
Intention_1	0.615	0.087	0.676	0.774	0.506	0.915	0.660	0.559	0.593	-0.145
Intention_2	0.516	0.245	0.564	0.663	0.386	0.896	0.546	0.512	0.536	-0.106
Intention_3	0.574	0.204	0.619	0.721	0.420	0.929	0.574	0.541	0.539	-0.136
Literacy_1	0.542	0.117	0.508	0.600	0.535	0.561	0.548	0.449	0.838	-0.177
Literacy_2	0.609	0.080	0.517	0.626	0.623	0.542	0.583	0.481	0.882	-0.231
Literacy_3	0.602	0.076	0.541	0.630	0.637	0.531	0.564	0.496	0.880	-0.257
Literacy_4	0.636	0.012	0.559	0.630	0.692	0.503	0.594	0.489	0.858	-0.296
Literacy_5	0.603	0.000	0.561	0.637	0.632	0.503	0.616	0.446	0.843	-0.267
Literacy_6	0.583	-0.038	0.521	0.596	0.650	0.451	0.571	0.408	0.819	-0.266
Literacy_7	0.561	0.066	0.521	0.616	0.582	0.498	0.514	0.443	0.778	-0.257
Perf_1	0.508	0.091	0.529	0.551	0.433	0.465	0.723	0.437	0.452	-0.151
Perf_2	0.644	0.044	0.687	0.708	0.588	0.610	0.908	0.605	0.626	-0.165
Perf_3	0.675	0.039	0.674	0.724	0.607	0.573	0.900	0.631	0.624	-0.159
Soc_1	0.531	0.263	0.546	0.580	0.398	0.541	0.586	0.902	0.473	-0.158
Soc_2	0.511	0.295	0.533	0.566	0.351	0.539	0.555	0.906	0.454	-0.116
Soc_3	0.594	0.103	0.580	0.573	0.565	0.471	0.619	0.829	0.519	-0.215

e-Lit x Efficacy	-0.173	0.001	-0.060	-0.135	$\bar{0.245}$	-0.037	$\bar{0.101}$	$\bar{0.094}$	$\bar{0.255}$	1.000
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Heterotrait-Monotrait Ratio (HTMT)

Lastly, to confirm that the measurement model is valid, the Heterotrait-Monotrait ratio (HTMT) was checked. The HTMT is the ratio of the average correlations between constructs that measure different concepts versus the average correlations of indicators measuring the same construct. The common threshold for good discriminant validity established by majority of researchers is $HTMT \leq .950$ (Kline, 2011). If the HTMT exceeds the threshold, it suggests that constructs overlap significantly and should be reconsidered. Table 9 shows the HTMT for this study and all the values are within the threshold.

Table 9

Discriminant Validity-Heterotrait-Monotrait ratio (HTMT)

	e-Lit x Effort								
	Anthro	Barrier	Benefit	Efficacy	Effort	Intention	Perf	Social	e-Lit
Anthro									
Barrier	0.153								
Benefit	0.788	0.158							
Efficacy	0.863	0.127	0.879						
Effort	0.769	0.258	0.675	0.761					
Intention	0.699	0.183	0.762	0.900	0.526				
Perf	0.856	0.188	0.894	0.948	0.748	0.763			
Social	0.713	0.246	0.731	0.767	0.562	0.670	0.801		
e-Lit	0.772	0.225	0.701	0.832	0.797	0.663	0.778	0.614	

e-Lit x	0.183	0.008	0.066	0.150	0.256	0.038	0.113	0.104	0.266
Efficacy									

Measurement Model Prediction

Findings from this study showed that the proposed integrated model effectively predicted the intentions to use health technology (sexual and reproductive health chatbot), supporting RQ 1. The model integrated HBM, UTAUT and CASA frameworks, using relevant constructs to build a predictive structural equation model. The analysis revealed that a $Q^2_{predict}$ value of 0.644, derived from the cross-validation when assessing the model's predictive power. According to Hair and Alamer (2022), a $Q^2_{predict}$ value of 0.500 and above is generally considered acceptable indicating a good predictive power. Hence, the result of 0.644 showed that the model explained 64.4% of the variance in the prediction of intentions. This demonstrated a moderately strong predictive power. The Root Mean Squared Error (RMSE) which measures the average magnitude of prediction errors showed a value of 0.598. This relatively low RMSE suggests that the model's prediction was close to actual values, supporting its accuracy. Lastly, the Mean Absolute Error (MAE) which represents the average absolute difference between predicted and actual values was 0.437. This indicated that the model's predictions only deviated by 0.437 units which was within an acceptable range. Table 10 below shows the model prediction highlighting that the proposed model was reliable and valid.

Table 10

Model Prediction

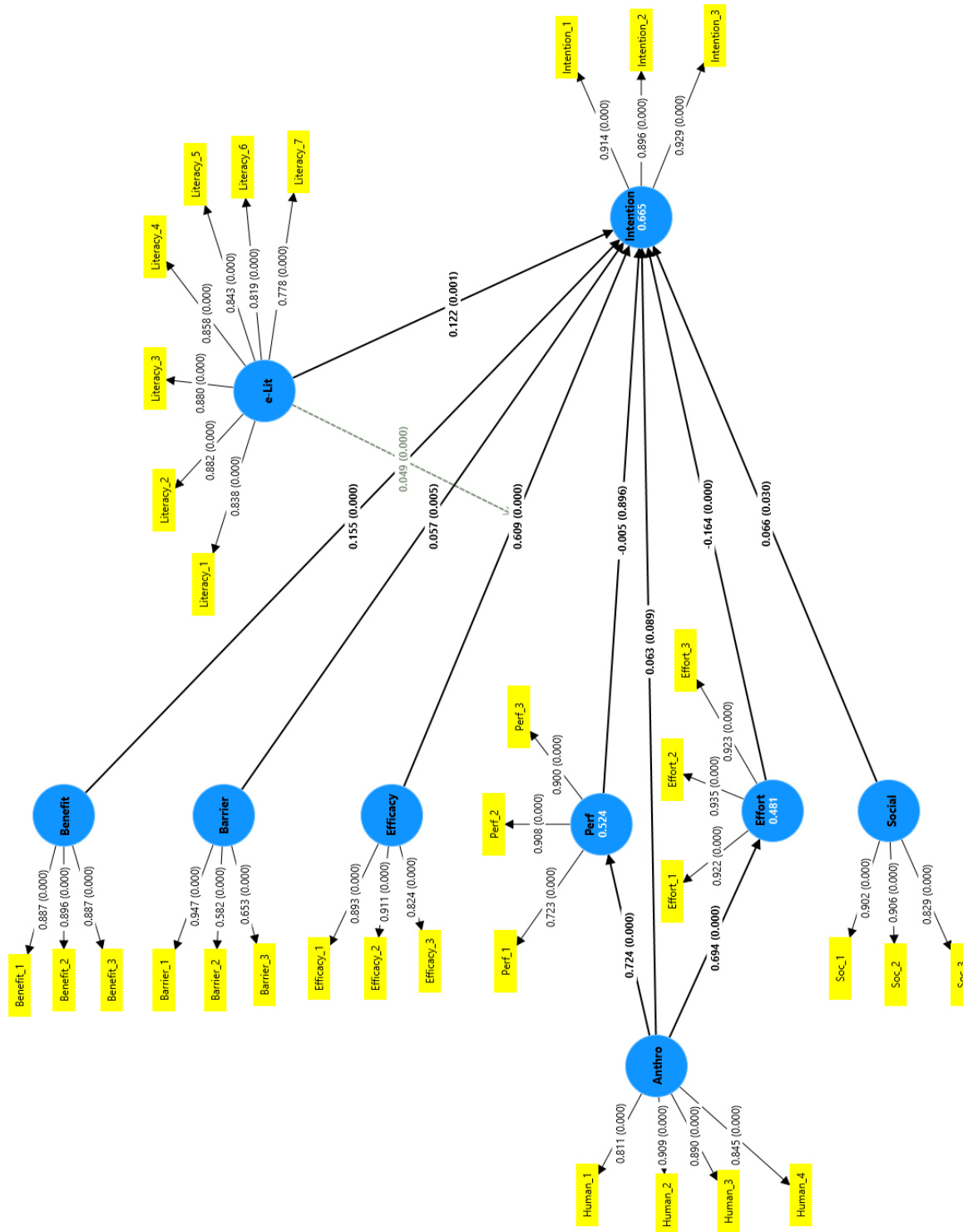
	$Q^2_{predict}$	RMSE	MAE
Intention	0.644	0.598	0.437

Structural Model

After establishing that the measurement model was reliable and valid, the next step was the evaluation of the structural path of the model. This process was necessary to examine the relationships between latent variables and assess if the suggested hypotheses had significance. Following Hair and colleagues' (2020) recommendations, the following steps were conducted (1). Examining the model for collinearity; (2). Assess the size and significance of paths; (3). Evaluate the coefficients of determination and (4). Examine the out-of-sample predictive power using the PLSpredict method (discussed in the theoretical implications section). Figure 11 illustrates the Structural Model developed using PLS-SEM version 4.0, representing the proposed integrated model.

Figure 11

PLS-SEM Structural Model



Examining Collinearity (Inner Model)

Collinearity occurs when several predictors are highly correlated leading to overlaps or redundancy of the information they provide. This can disrupt the path coefficient estimation, reducing the interpretability of the model and affecting the unique effect of each predictor against the dependent or outcome variable (Hair et al., 2022). The Variance of Inflation Factors (VIF) should be less than 5 to show low collinearity. Table 11 shows the VIF of all values, ranging from 1.000 to 3.860, revealing that there is no high collinearity between the predictors in the model.

Table 11

Collinearity Statistics (VIF)-Inner Model

	Anthro	Barrier	Benefit	Efficacy	Effort	Intention	Perf	Social	e-Lit	e-Lit x Effort
Anthro					1.000		1.000			
Barrier						1.169				
Benefit						2.893				
Efficacy						3.860				
Effort						2.743				
Intention										
Perf							3.470			
Social							2.140			
e-Lit							2.903			
e-Lit x Effort							1.168			

Significance of Paths

The next step was to examine the significance and relevance of the structural model relationships, determining if the hypotheses were supported by the data. This involved assessing the strength of path coefficients and statistical significance through running a bootstrapping procedure, computing t-statistics and p-values. Table 12 shows a detailed summary of the significance of each path as well as effect sizes, highlighting key relationships in the structural model.

H1 evaluated whether anthropomorphism was positively related to performance expectancy. The results revealed that anthropomorphism had a significant and positive impact on performance expectancy ($\beta=.724$, $t=41.594$, $p<.001$). Hence, H1 was supported.

H2 evaluated if anthropomorphism was positively related to effort expectancy. The results showed that anthropomorphism had a significant and positive impact on effort expectancy ($\beta=.694$, $t=33.623$, $p<.001$). Hence, H2 was supported.

H3 evaluated if performance expectancy was positively related to intentions to use a sexual and reproductive health chatbot. The results revealed that performance expectancy did not have a significant impact on intention ($\beta= -.005$, $t=0.131$, $p=.448$). Hence, H3 was not supported.

H4 evaluated if effort expectancy was positively related to intentions to use a sexual and reproductive health chatbot. The results showed that effort expectancy had a negative and significant impact on intentions ($\beta=-.164$, $t=4.742$, $p<.001$). Hence, H4 was not supported.

H5 evaluated if social influence was positively related to intentions to use a sexual and reproductive health chatbot. The results showed that social influence had a positive and significant impact on intentions ($\beta=.066$, $t=2.177$, $p<.050$). Hence, H5 was supported.

H6 evaluated if perceived benefits were positively related to intentions to use a sexual and reproductive health chatbot. The results showed that perceived benefits had a positive and significant impact on intentions ($\beta=.155$, $t=4.225$, $p<.001$). Hence, H6 was supported.

H7 evaluated if perceived barriers were negatively related to intentions to use a sexual and reproductive health chatbot. The results showed that perceived barriers had a significant impact on intentions, but it was positive ($\beta=.057$, $t=2.788$, $p<.050$). Hence, H7 was not supported.

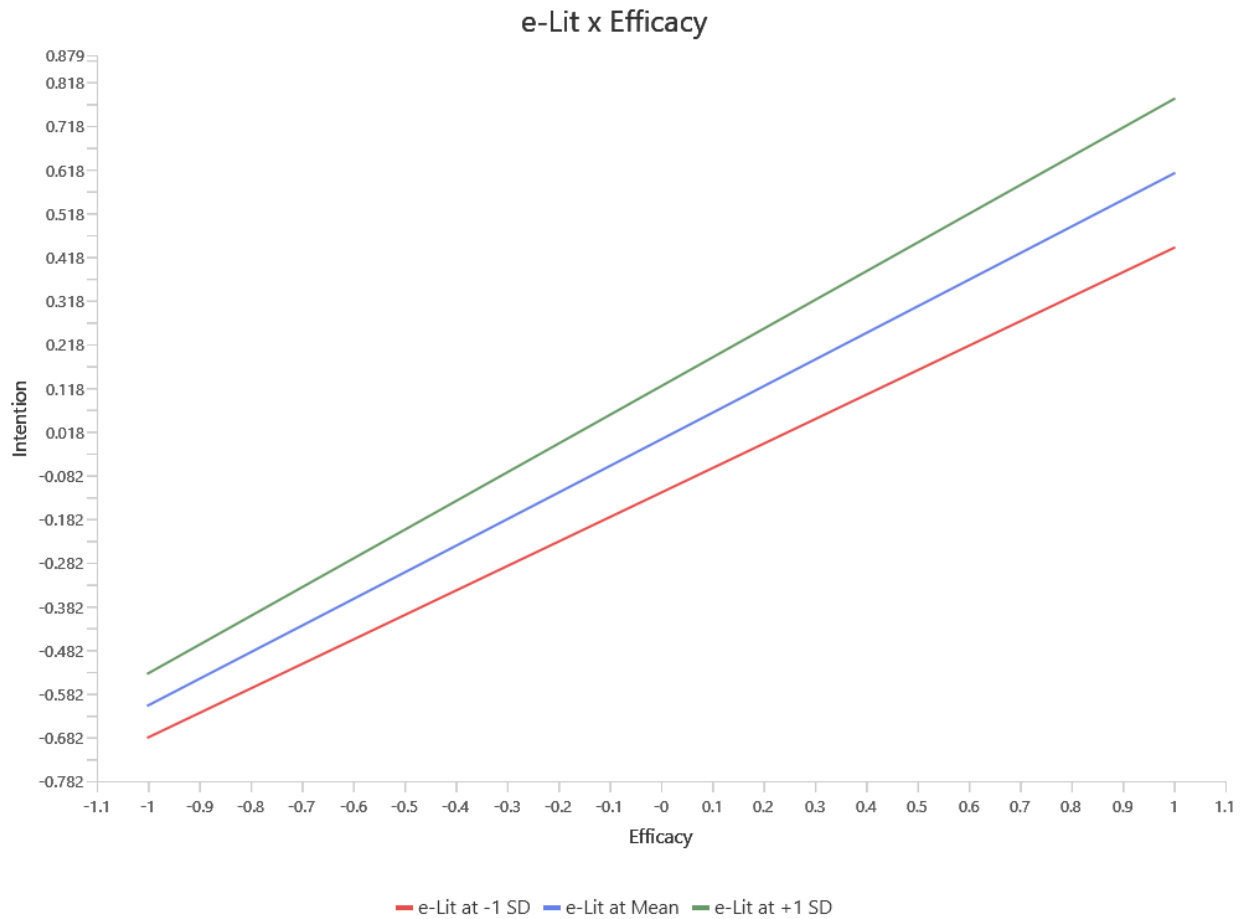
H8 evaluated if self-efficacy was positively related to intentions to use a sexual and reproductive health chatbot. The results showed that self-efficacy had a positive and significant impact on intentions ($\beta=.609$, $t=15.228$, $p<.001$). Hence, H8 was supported.

H9 evaluated if e-health literacy moderates self-efficacy with behavioral intentions. Upon conducting a moderation analysis, the results showed that e-health literacy significantly moderated the relationship between self-efficacy and behavioral intentions ($\beta=.049$, $t=3.664$, $p<.001$). Hence, H9 was supported. Figure 12 represents a slope analysis to further represent e-health literacy as a significant moderator in this relationship. The slope analysis revealed that the strength of the relationship between self-efficacy and behavioral intentions varied depending on individuals' levels of e-health literacy. Among those with high e-health literacy, the slope was steep and positive, indicating a strong relationship between self-efficacy and behavioral intentions—suggesting that as self-efficacy increases, intention to use the chatbot increases significantly.

Table 12*Constructs and Paths*

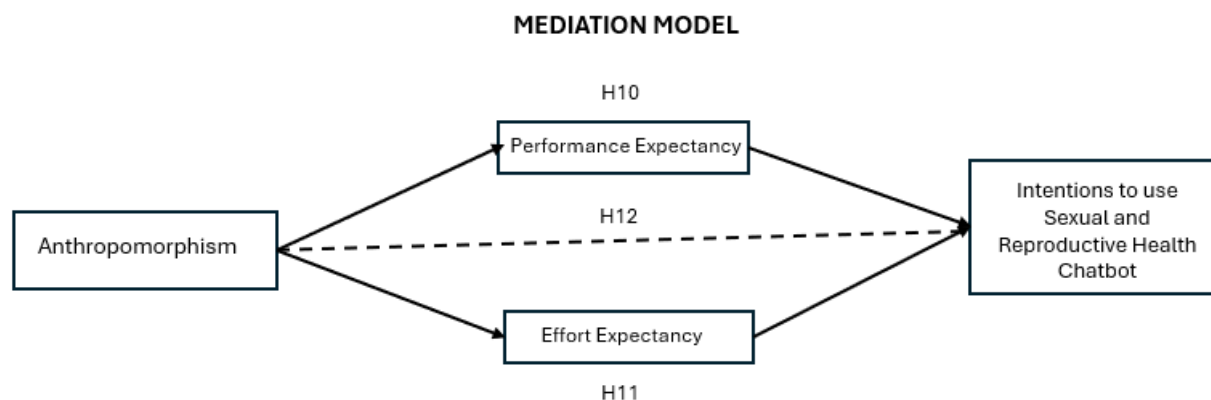
Hypothesis	Path coefficient	Standard deviation	T statistics	P values
Anthro -> Perf	0.724	0.017	41.594	0.000
Anthro -> Effort	0.694	0.021	33.623	0.000
Perf -> Intention	-0.005	0.039	0.131	0.448
Effort -> Intention	-0.164	0.035	4.742	0.000
Social -> Intention	0.066	0.030	2.177	0.030
Benefit -> Intention	0.155	0.037	4.225	0.000
Barrier -> Intention	0.057	0.040	2.788	0.003
Efficacy -> Intention	0.609	0.039	15.228	0.000
e-Lit x Efficacy -> Intention	0.049	0.013	3.664	0.000
Anthro -> Intention	0.063	0.037	1.700	0.045

Figure 12
Moderation Slope Analysis



Mediation Analysis

A mediation analysis was conducted to test the mediating role of performance expectancy and effort expectancy respectively in the relationship between anthropomorphism and intentions to use a sexual and reproductive health chatbot. The direct relationship between anthropomorphism and intentions to use a sexual and reproductive health chatbot was also tested. Figure 13 shows the proposed mediation model.

Figure 13*Proposed Mediation Model*

H10 examined if performance expectancy mediated the relationship between anthropomorphism and the intention to use a sexual and reproductive health chatbot. While H11 examined if effort expectancy mediated the relationship between anthropomorphism and the intention to use a sexual and reproductive health chatbot. H12 examined direct effects by assessing if anthropomorphism was positively related to intentions to use a sexual and reproductive health chatbot.

The results (Table 13) showed no significant indirect effect on (H10) performance expectancy and intention to use a sexual and reproductive health chatbot (H10: $\beta = -.003$, $t = .112$, $p = .911$). The total effect of anthropomorphism to intention to use a sexual and reproductive health chatbot (H12) was not significant ($\beta = .063$, $t = 1.275$, $p = .203$). With the inclusion of the mediating effect, the direct effect was still not significant ($\beta = -.059$, $t = 1.686$, $p = .092$). This showed that performance expectancy was not a significant mediator between anthropomorphism and the intention to use a sexual and reproductive health chatbot and H10 and H12 were not supported.

There was a significant indirect effect on (H11) effort expectancy and intention to use a sexual and reproductive health chatbot (H11: $\beta = -.119$, $t = 4.656$, $p < 0.001$). The total effect of anthropomorphism to intention to use a sexual and reproductive health chatbot (H12) was not significant ($\beta = .063$, $t = 1.275$, $p = .203$). There was also no significant direct effect from (H12) anthropomorphism to intention to use a sexual and reproductive health chatbot ($\beta = -.059$, $t = 1.275$, $p = .203$). Hence, H11 was supported and showed that effort expectancy fully mediated the relationship between anthropomorphism and intentions to use a sexual and reproductive health chatbot.

Table 13

Mediation Analysis Results

Total effects (Anthro -> Intention)			Direct effect (Anthro -> Intention)			Hypothesis	Indirect effect				Percentile bootstrap 95% confidence interval	
Coefficient	T value	p value	Coefficient	T value	p value		Coefficient	SE	T value	p value	Lower	Upper
.063	1.275	.203	-.059	1.686	.092	Anthro -> Performance -> Intention	-.003	.029	.112	.911	-.060	.053
.063	1.275	.203	-.059	1.686	.092	Anthro -> Effort -> Intention	-.119	.025	4.654	.000	-.170	-.069

Key Findings and Implications

Findings revealed that anthropomorphism or humanlike characteristics of a chatbot had a significant influence in performance expectancy and effort expectancy (H1 and H2) when it involved the functionality of the chatbot. While previous studies showed that there were differing viewpoints from the perspective of anthropomorphism and its impact on the usability or functionality of the chatbot (Blut et al., 2021; Katsyri et al., 2015), the findings from this study confirmed that the presence of human-like characteristics can enhance the ease of use and overall performance expectations of a chatbot. The human-like features in technology can foster a sense of familiarity and relatability, creating an environment of trust and engagement (Goel & Garg, 2025). This finding also affirms that anthropomorphic features should be considered from a design perspective when developing health technology because this characteristic could help users navigate sensitive sexual and reproductive health more intuitively, ultimately increasing intentions to use the digital product to manage one's healthcare.

Furthermore, the focus on incorporating warmth and empathy as key components of the anthropomorphism feature highlighted its potential to bridge the gap between human and chatbot communication (Janson, 2023). These qualities are crucial in helping users feel more understood and supported especially with regards to sensitive health topics where empathy has stimulated deeper engagement from the user, fostering a sense of social interaction and reducing the perceived psychological distance between human and technology (chatbot) (Haque et al., 2023). Subsequent research could incorporate further details about human chatbot communication through exploring specific anthropomorphic conversational styles that could increase self-disclosure and improve overall experience using chatbots to manage one's health.

Performance expectancy alone was not a significant predictor of intentions to use a sexual and reproductive health chatbot in silo (H3) showing that there could be other factors that affected users' decisions to the chatbot. While anthropomorphic features could improve the users' evaluations of chatbot utility, these evaluations alone do not carry enough motivational weight to drive usage intentions. The mediation analysis also showed that performance expectancy did not mediate the path between anthropomorphism and intentions (H10). Performance expectancy is about how effective and useful a user might perceive the digital product to be when trying to achieve a task or goal (Venkatesh et al., 2016). Given the nature and purpose of the chatbot, users may prioritize factors such as accuracy and relevance of information or reliability of the technology to manage sexual and reproductive health. These factors may override anthropomorphic features when users want to achieve their health goals, assessing intentions to use the chatbot based on its core purpose of delivering trustworthy and actionable health support, independent of how human-like the human-chatbot interaction appears to be (Kim, 2024).

On the other hand, effort expectancy, which is the degree of ease associated with using technology (Venkatesh et al., 2016), was a partially significant predictor of intentions to use the chatbot (H4). The relationship between effort expectancy and intentions to use the chatbot was negative. Prior research and their findings showed how functional complexities of digital products and how ease of navigation could increase usability and accessibility when engaging in technology (De Angelis et al., 2024). This finding was counterintuitive and diverges from traditional technology acceptance theories. One possible reason could be how participants may have perceived the chatbot as overly simplified, undermining its seriousness or credibility. In

highly sensitive situations such as discussing SRH topics, users may associate slightly more effort with increased value of trustworthiness.

When tested in a mediation analysis, effort expectancy was also a significant mediator between anthropomorphism and intentions to use the sexual and reproductive chatbot (H11). This finding underscores the critical interplay between interactional and functional factors in adopting sensitive health technology. Interactional features such as anthropomorphism enhance human-like communication and a sense of empathetic engagement, making the interaction more relatable and less transactional in situations where users might feel hesitant or vulnerable. However, the influence of anthropomorphism on user behavior or intentions to use a sexual and reproductive health chatbot is not significant as a predictor when examined alone (H12). Its significance was amplified with ease of navigation (Effort expectancy) and intuitive interaction. This interplay suggests that users may perceive anthropomorphic features as more impactful when they do not experience any barriers or challenges related to the chatbot's complexity or functionality. While users may appreciate empathetic tones of chatbot communication, they may be deterred from using the chatbot if it is difficult to navigate or require excessive effort to accomplish their objectives on the chatbot. This finding broadens the scope of understanding in health communication and technology design, highlighting the need of a dual approach between interactional and functional attributes when examining intentions to use a health chatbot. These interconnected elements collectively shape user behavior.

These findings challenge traditional technology acceptance models, which often emphasize performance or effort expectancy as a central predictor of adoption or usage intentions. Instead, it highlights the need to broaden these frameworks by incorporating psychological and emotional factors, such as trust, empathy, and relational engagement. These

elements are particularly critical in health chatbot communication and design, where users are navigating private and often vulnerable topics. Recognizing and addressing these relational dimensions can enhance the overall user experience and drive adoption in meaningful ways.

Social influence prefaces that an individual will have the intention to use a particular technology if people they trust such as friends, family or healthcare providers recommend that they should use that technology as it is a valuable resource (Venkatesh et al., 2016). This social influence and endorsement underscore the role of social dynamics in influencing behavior and decision-making processes (Cao et al., 2024). In this study, social influence was a significant predictor in influencing intentions to use the chatbot (H5), aligning with the UTAUT theory (Venkatesh et al., 2012). It expands on the importance of how social influence could easily increase the uptake of a health product and avoid the underutilization of it. Sexual and reproductive digital products include sensitive health topics that can make users feel uncomfortable and vulnerable (Bennett et al., 2023). Hence, social influence plays a pivotal role in decision-making, creating a sense of validation and reassurance when one's trusted circle endorses this product as a social norm. In sensitive health domains such as sexual and reproductive health where stigma and judgement exist, positive social reinforcement, such as when a trusted peer or health provider shares a positive review or experience using a product, it reduces hesitation or fear of judgement, increasing usage intentions.

The findings for the health attributes showed that perceived benefits (H6) and self-efficacy (H8) were significant indicators of intentions to use a sexual and reproductive health chatbot. Using a sexual and reproductive health chatbot could reduce stigma, increase convenience and empower users through gaining knowledge and making more informed health decisions (Mills et al., 2023). Self-efficacy represents the user's confidence in their ability to

successfully navigate the chatbot to achieve their sexual and reproductive health goals (Champion & Skinner, 2008). When users feel competent and capable of navigating the chatbot, they are more likely to have positive intentions towards using it.

However, perceived barriers (H7) were not supported as it showed a statistically significant positive relationship with behavioral intention. This unexpected result suggests that for some users, greater recognition of systemic or interpersonal barriers to SRH services may increase openness to alternative solutions like chatbots. In this context, perceived barriers may act as motivational cues, prompting individuals to seek safer, more accessible, anonymous, or cost-effective alternatives to traditional in-person care. It is also possible that the perceived barriers measured in this study reflect awareness of challenges rather than a sense of helplessness, encouraging users to seek digital options as proactive workarounds.

Findings showed that digital health literacy (also known as e-health literacy) was a significant moderator between self-efficacy and intentions to use a sexual and reproductive health chatbot (H9). Digital health literacy has been known to shape individual's intentions to use digital interventions or products for better health outcomes (Sieck et al., 2021) while self-efficacy refers to an individual's confidence and ability to successfully perform an action (Champion & Skinner, 2008). This shows that digital health literacy increases a user's confidence in navigating health technology, thereby strengthening their intentions to use it. Similarly, previous studies have indicated that digital health literacy and feeling self-efficacious to use digital health products were critical in determining usage intentions (Taba et al., 2022). Digital health literacy not only enhanced users' ability to understand and navigate online platforms but also bolstered users' confidence when utilizing this technology (Yuen et al., 2024). When users felt knowledgeable and capable of engaging with digital health products, their self-

efficacy strengthened, which in turn positively influenced their willingness and motivation to adopt and use these technologies (Rieder et al., 2020). This finding shows the synergistic and moderating relationship between digital health literacy and self-efficacy, underscoring the importance of accounting for varying levels of digital health literacy when examining usage intentions in this context. It challenges the assumptions often implicit in many theoretical frameworks which overlook this nuanced role of digital health literacy in shaping user confidence and overall motivation to engage with such health technology.

Theoretical Implications

These findings suggest that the proposed integrated model was robust and provided a reliable framework for understanding and predicting intentions to use health technology and more specifically, sexual and reproductive health chatbots. The findings pave the way for researchers to adapt this model for various health technologies, examining and developing more targeted and user-friendly digital products. Given the model's success in predicting usage intentions, researchers could utilize this model to enhance user engagement with various technological features found in similar health communication tools.

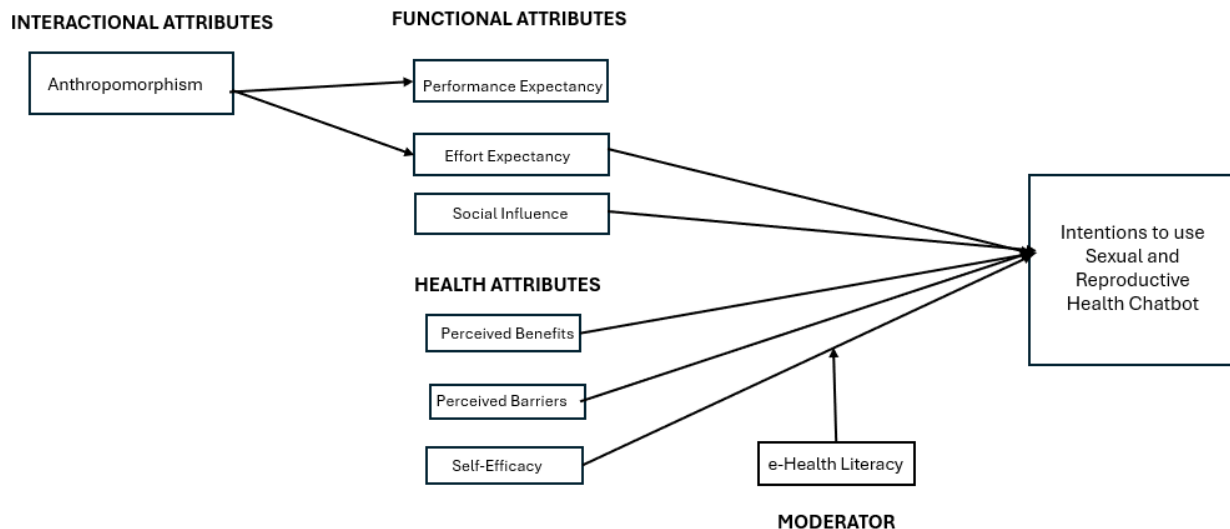
Figure 14*New Integrated Theoretical Model*

Figure 14 shows the new integrated model combining the key constructs from the Health Belief Model (HBM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Computers Are Social Actors (CASA) framework to provide a comprehensive understanding of users' intentions to adopt sexual and reproductive health chatbots. The model underscores how anthropomorphic design elements enhance chatbot functionality and emotional relatability, fostering a sense of familiarity that can improve trust and increase motivation for use. Additionally, effort expectancy serves as a mediating factor, reinforcing the need for seamless and intuitive chatbot interactions that minimize cognitive burden. The model's strong predictive power ($Q^2_{\text{predict}} = 0.644$, $RMSE = 0.598$, $MAE = 0.437$) suggests that an effective balance between technical efficiency and human-centered cues is crucial for driving adoption of digital health interventions. The proposed model makes significant academic contributions by bridging gaps between established technology adoption frameworks and emerging considerations in health technology design. Theoretically, it extends the HBM, UTAUT, and CASA frameworks

by demonstrating that traditional constructs such as performance expectancy and effort expectancy are not sufficient standalone predictors of health chatbot adoption. This challenges conventional utility-driven adoption models, emphasizing that psychological, emotional, and relational dynamics play an equally crucial role in technology engagement, particularly when users are navigating stigmatized or private health concerns. This model offers a new predictive framework that can be adapted across different health technologies, providing a validated and empirically tested approach to understanding digital health adoption. This also supports RQ1 showing that the proposed integrated theoretical framework largely accounts for intentions to use the sexual and reproductive health chatbot to manage sexual and reproductive health.

Practical Implications

These findings offer valuable insights into advancing health communication strategies through the design and implementation of sexual and reproductive health chatbots as well as other similar health technologies. Incorporating anthropomorphic features, which had the strongest path coefficients, showed that it could increase motivation and usage intentions. These features make users interactions more intuitive and empathetic, increasing engagement and self-disclosure (Kolomaznik et al., 2024). By stimulating aspects of human communication, anthropomorphic features can create an environment of trust and comfort when users navigate sensitive health topics (Li et al., 2023). The study showed that anthropomorphism is best paired with performance and effort expectancy, underscoring the importance of creating chatbots that are not only functional but also emotionally supportive and relatable to help bridge the gap between humans and technology. Incorporating these features is not just a design choice but a strategic approach towards building trust and rapport among users.

For health communication and health technology researchers, this could shift towards integrating such interactional features to cater to the user's psychological and emotional needs while maintaining the chatbot's core functional purpose. This can also lead to more effective health communication tools, increasing usage and empowering users to take control of their own health through sustained usage of health technologies. Empowering users was also a strong predictor of intentions with digital health literacy acting as a moderating factor. This highlights the importance of increasing digital health literacy among users in order to build confidence and reduce the underutilization of such health technologies. Other factors that could increase self-efficacy such as data privacy or similar design features to accentuate privacy should be considered too. Ultimately, the findings advocate for the development of tailored and user-centered strategies that integrate health, functional and interactional attributes. This approach can help to create inclusive health technologies catered to diverse user needs, drive adoption and improve health outcomes.

CHAPTER 6

Results

Quantitative Study of LGBTQ+ Subgroup

The following section assesses the structural model to identify if the intentions to use a SRH chatbot differ for LGBTQ+ individuals in the context of SRH management (RQ2).

Figure 15 below shows the structural model for the LGBTQ+ individuals with Table 14 indicating the constructs and paths.

RQ2: Does the structural model for intentions to use a sexual and reproductive health chatbot differ for LGBTQ+ individuals in the context of sexual and reproductive health management?

Figure 15

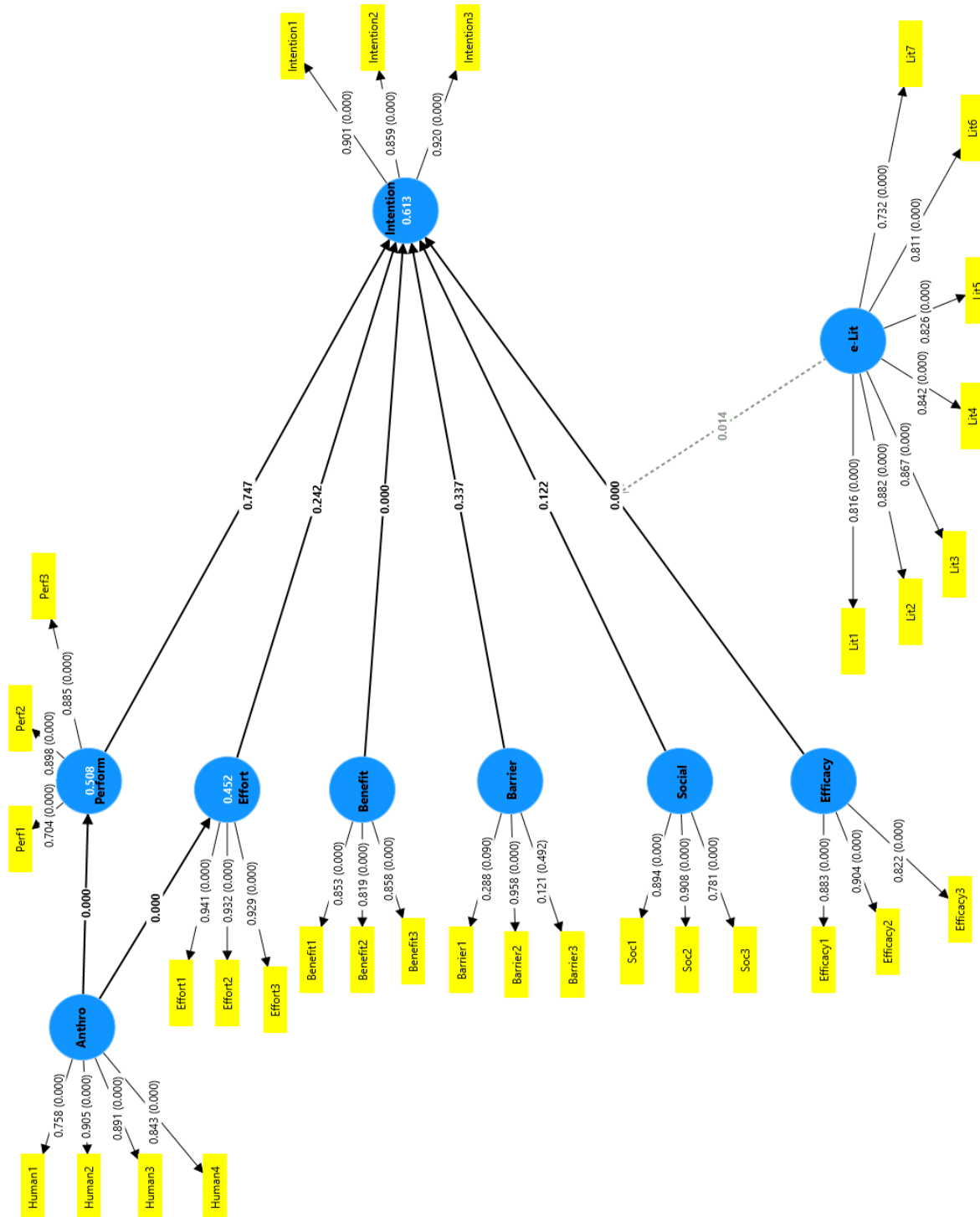
LGBTQ+ Structural Model

Table 14*LGBTQ+ Constructs and Paths*

Hypothesis	Path Coefficient	Standard deviation	T statistics	P values
Anthro -> Perform	0.713	0.032	22.320	0.000
Anthro -> Effort	0.673	0.040	16.992	0.000
Perform -> Intention	-0.023	0.070	0.322	0.747
Effort -> Intention	-0.080	0.068	1.170	0.242
Social -> Intention	0.079	0.051	1.547	0.122
Benefit -> Intention	0.339	0.071	4.784	0.000
Barrier -> Intention	-0.060	0.063	0.959	0.337
Efficacy -> Intention	0.579	0.067	8.604	0.000
e-Lit x Efficacy -> Intention	0.060	0.024	2.453	0.014

Significance of Paths- LGBTQ+

Similar to the general population surveyed, H1 which evaluated anthropomorphism was positively related to performance expectancy ($\beta=.713$, $t=22.320$, $p<.001$) and H2 which evaluated if anthropomorphism was positively related to effort expectancy ($\beta=.673$, $t=16.992$, $p<.001$) were both supported.

H3 which evaluated if performance expectancy was positively related to intentions to use a sexual and reproductive health chatbot ($\beta= -.023$, $t=0.322$, $p=.747$) was not supported. This was similar to the general population.

H4 which tested if performance expectancy was positive and significantly related to intentions to use a sexual and reproductive health chatbot was not supported ($\beta=-.080$, $t=1.170$, $p=.242$), similar to the general population. H5 which tested if social influence was positively related to intentions to use a sexual and reproductive health chatbot ($\beta=.079$, $t=1.547$, $p=.122$) was not supported. This was different from the general population.

While H6 which evaluated if perceived benefits were positively related to intentions to use a sexual and reproductive health chatbot, was supported and showed significant results ($\beta=.399$, $t=4.784$, $p<.001$), H7 which tested perceived barriers were negatively related to intentions to use a sexual and reproductive health chatbot was not significant or supported ($\beta=-.060$, $t=.959$, $p=.337$). This was both similar to the general population.

H8 evaluated if self-efficacy was positively related to intentions to use a sexual and reproductive health chatbot. The results showed that self-efficacy had a positive and significant impact on intentions ($\beta=.579$, $t=8.604$, $p<.001$). Similar to the general population, H8 was supported.

H9 evaluated if e-health literacy moderates self-efficacy with behavioral intentions. Upon conducting a moderation analysis, the results showed that e-health literacy significantly moderated the relationship between self-efficacy and behavioral intentions ($\beta=.060$, $t=2.453$, $p<.005$). Similar to the general population, H9 was supported.

Mediation Analysis- LGBTQ+

A mediation analysis was conducted to examine performance and effort expectancy as mediators, testing the significance of the relationship between anthropomorphism and intentions to use a sexual and reproductive health chatbot among the LGBTQ+ population. The direct

impact of anthropomorphism on intentions to use a sexual and reproductive health chatbot was also assessed to understand its impact within the LGBTQ+ community.

The results (Table 15) showed no significant indirect effect on (H10) performance expectancy and intention to use a sexual and reproductive health chatbot ($\beta=-.003$, $t=.062$, $p=.950$). The total effect of anthropomorphism to intention to use a sexual and reproductive health chatbot (H12) was not significant ($\beta=-.114$, $t=1.445$, $p=.148$). With the inclusion of the mediating effect, the direct effect was still not significant ($\beta=-.069$, $t=.958$, $p=.338$). This showed that performance expectancy was not a significant mediator between anthropomorphism and the intention to use a sexual and reproductive health chatbot and H10 and H12 were not supported similar to the general population.

There was no significant indirect effect on (H11) effort expectancy and intention to use a sexual and reproductive health chatbot (H1: $\beta=-.042$, $t=.886$, $p=.376$). The total effect of anthropomorphism to intention to use a sexual and reproductive health chatbot (H12) was not significant ($\beta=-.114$, $t=1.445$, $p=.148$). There was also no significant direct effect from (H12) anthropomorphism to intention to use a sexual and reproductive health chatbot ($\beta=-.069$, $t=.958$, $p=.338$). Hence, H11 was not supported. This showed that both performance expectancy and effort expectancy did not mediate the relationship between anthropomorphism and intentions to use a sexual and reproductive health chatbot unlike the general population.

Table 15

Mediation Analysis Results

Total effects (Anthro -> Intention)			Direct effect (Anthro -> Intention)				Indirect effect				Percentile bootstrap 95% confidence interval	
Coefficient	T value	p value	Coefficient	T value	p value	Hypothesis	Coefficient	SE	T value	p value	Lower	Upper

-.114	1.445	.148	-.069	.958	.338	Anthro -> Performance -> Intention	-.003	.052	.062	.950	-.135	.053
-.114	1.445	.148	-.069	.958	.338	Anthro -> Effort -> Intention	-.042	.048	.886	.376	-.105	-.099

Key Findings and Implications

The LGBTQ+ community is a disparity group that has often face healthcare biases and limited access to competent and inclusive care in the sexual and reproductive health domain (Taylor & King, 2021). With the rise of digital health technologies such as chatbots, it provides the opportunity for LGBTQ+ individuals to have access to confidential and stigma-free health resources. Understanding how LGBTQ+ individuals interact with such technologies would be essential to optimize the maximum effectiveness of how digital health resources could increase accessible healthcare for the community. The findings examined the structural model of the integrated framework and focused on the structural model impacted the LGBTQ+ subgroup, honing into key factors that predicted intentions to use a chatbot to manage one's sexual and reproductive healthcare.

A key finding that emerged from the analysis showed that anthropomorphism enhanced perceptions but did not individually drive intentions to use the chatbot. This finding was similar to the analysis conducted with the general population. Anthropomorphism or the “humanistic characteristics” of a chatbot had a significant impact on the user's perceived functional aspects of the chatbot (performance and effort expectancy), showing how the human-like nature of the chatbot increased its ease of use. However, it was not a primary driver contributing to LGBTQ individuals' intentions to use the chatbot. LGBTQ+ individuals have historically faced discrimination in the sexual and reproductive health space; hence other factors might have more impact in driving the adoption and engagement of the chatbot. While anthropomorphism helps to

improve user experience, when in silo, it might not increase feelings of safety or trust when communicating or disclosing sensitive information to the chatbot. Alongside making chatbots more human-like, designing them with LGBTQ+ affirming communication strategies could be a strategy to increase engagement. Including relational communication elements such as empathy-driven messages or adaptive response styles could aid the anthropomorphism factor, increasing interaction.

Social influence was also not a significant predictor of chatbot use for LGBTQ+ individuals. Social influence was a factor adopted from the UTAUT model that highlighted the degree to which an individual's desire to use a technology was affected by the opinions of those in their social groups (Bhandari et al., 2024). Following experiences of mistrust in the medical environment and the lack of inclusivity (Matsuzaka et al., 2021), LGBTQ+ individuals might choose to seek healthcare or decide on what type of health technology to use privately, based on their individual needs. Additionally, sexual and reproductive health is a sensitive issue that individuals might not be comfortable openly discussing with their social groups. This could lead to an increased use of private and confidential health technology such as chatbots, where individuals can access tailored information, regardless of whether they receive approval from their social group.

While perceived benefits showed significance in driving intentions to use the sexual and reproductive health chatbot, perceived barriers did not deter usage either. Perceived barriers, a predictor from HBM, refer to the individual's belief about the obstacles associated with adopting health behavior (Karl et al., 2022). However, in this context, LGBTQ+ individuals may agree that such barriers do not significantly discourage adoption, suggesting that the perceived benefits of using a chatbot such as anonymity, tailored and inclusive health information and accessibility

outweighs any potential obstacles. Unlike traditional healthcare systems, chatbots provide a space for LGBTQ+ individuals to control their communication and interaction without bearing the brunt of judgment. This increased autonomy adds to the perceived benefits of a private and accessible health resource, overcoming logistical and psychological barriers present in traditional health-seeking experiences.

Lastly, similar to the general population, self-efficacy sufficed as a strong significant predictor for chatbot use within the LGBTQ+ community. This was significantly moderated by e-health literacy, showing its importance in ensuring that individuals are equipped with digital skills to adapt to the evolving healthcare landscape. When individuals have a higher level of digital health literacy, they are more likely to be more confident in interacting with health technology because they have the necessary skills to understand and navigate the resource better (Kim & Xie., 2017). Higher levels of e-health literacy would empower individuals to understand the features and functionalities of a health chatbot, increasing the likelihood of integrating such digital resources into their health management routines (Niltakan, 2024). Healthcare interventions are increasingly shifting towards digital platforms, and the lack of e-health literacy could result in the underutilization of such resources. For the LGBTQ+ community who already experience disparities and barriers in traditional healthcare, enhancing e-health literacy and equipping individuals with the relevant digital skills could provide additional avenues for them to seek healthcare their needs. This finding highlights the importance of prioritizing digital skill-building and integrating digital health skills into health education initiatives, ensuring that individuals can confidently access digital resources for their health.

Overall, the structural model does differ when tested among the LGBTQ+ population (RQ2). This highlights the need for more tailored and inclusive digital interventions for various

subgroups, especially in the sexual and reproductive health domain. While chatbots present promising opportunities for inclusive and stigma-free healthcare, their adoption and usage vary based on the unique characteristics of the adopting population. With the specific challenges experienced by the LGBTQ+ population when seeking sexual and reproductive health care, it is important to understand these challenges and implement relevant solutions when designing the chatbot.

Beyond just feature designs, communication designs are equally important in shaping human chatbot interactions. Human chatbot communication should display reassurance and empathy, using inclusive language to encourage a safe space when discussing sensitive health issues (Branley-Bell et al., 2023). In order to generate accurate and adaptive response strategies, chatbots should use personalized and approachable messages to encourage self-disclosure. Leveraging natural language processing (NLP) and machine learning algorithms to interpret user input, the chatbot depends largely on user communication to provide detailed and tailored information. Thus, a warm and empathetic interaction encouraging self-disclosure could improve the accuracy and precision of health information. Such user-centered communication strategy could help to enhance inclusive digital resources for subgroups such as the LGBTQ+ community, creating an alternative health resource they can rely on for stigma-free and accessible sexual and reproductive healthcare.

CHAPTER 7

Findings

Qualitative Study

Despite the ongoing debate between the value of empathy in chatbots, chatbot message design has not been evaluated extensively through a qualitative lens. Hence, this section of the dissertation hones into exploring empathetic and non-empathetic chatbot messages, with and without emojis could affect the quality of HMC. Evaluating these aspects of chatbot design can improve message framing by finding an optimal balance between anthropomorphizing technology while maintaining a professional and effective digital health intervention. This will help to yield practical insights into optimizing chatbot communication for diverse health interventions, ultimately improving engagement and user satisfaction.

Research Questions:

RQ1: How do empathetic versus non-empathetic communication styles in chatbot influence users' intentions to self-disclose and engage with a sexual and reproductive health chatbot?

RQ2: What are users' perceptions of human-like communication styles simulated by the chatbot, and how do these perceptions shape their decision to engage with a sexual and reproductive health chatbot?

RQ3: How do personalized responses enhance user satisfaction and intentions to use a sexual and reproductive health chatbot?

RQ4: What insights can be drawn from user feedback regarding the effectiveness of empathetic and non-empathetic messages in fostering trust and increasing intentions to use a sexual and reproductive health chatbot?

Findings

Preferred Design and Emotional Impact

These findings were from the qualitative survey. There were mixed opinions when participants were asked about their preferred message design. Some participants described the non-empathetic message design as “informational”, “impersonal” and “straightforward”, labeling this interaction as time-efficient and helpful when seeking SRH information. Participants who preferred this message design also indicated that this interaction felt as if they were speaking to a healthcare provider as most healthcare providers, they had interacted with exhibited a professional and informational style of communication. As a result, they felt that this factual message design without emotional embellishments was reliable. Participants who preferred the empathetic message design highlighted their increased willingness to engage with the chatbot as it was more “welcoming” and “human-like”. They emphasized that the use of “emojis” provided an added layer of emotional understanding while the empathetic tone created a sense of being “heard and understood”. Overall, the use of empathetic messaging developed social support and reassurance which participants felt would be a beneficial trait to have when communicating about sensitive SRH topics.

Suitability for Discussing Sensitive Topics

The topic chosen for the message designs were about birth control which is a commonly discussed sensitive SRH topic among young adult users on digital health interventions. Participants who preferred the non-empathetic message alluded to it being direct and neutral, hence making the overall experience discussing this sensitive topic less “weird” or “awkward”. They also felt that the use of a neutral and information tone felt “less judgmental” as it was “not overly patronizing or personal”. Participants who preferred the empathetic message had

contrasting opinions. One respondent included that the empathetic tone made them feel as if they were conversing with a friend as compared to speaking with a healthcare provider in a sterile and serious environment. This increased their willingness to “talk more” with the chatbot. This underscored how empathetic messages exchanged between the chatbot and users could stimulate a safe and reassured environment for self-disclosure. Additionally, this highlighted how anthropomorphic interactions between chatbots, and humans could contribute to relational and emotional dynamics where participants felt they were being “heard”, and that their well-being was being prioritized.

Human-Like Elements and Comfort Levels

When asked about how they felt about the human-like characteristics shown by the chatbot through the messages, participants identified phrases that features which they found impactful. Many participants were quick to state that the use of emojis and casual language such as “I’m here for you” were unique as it sounded like how “their friend would speak or communicate” with them. These elements made the chatbot “feel more human” rather than a machine which would have increased participants’ comfort levels and willingness to discuss SRH topics. There were a smaller group of participants that did not find this appealing as emojis were seen as “unprofessional” and “almost as if underplaying the importance of their conversations”. The overly friendly tone also seemed to cross a threshold for some participants who mentioned that “the emojis were too much for me”. This highlighted the importance of finding a balance between empathetic and overly friendly emoji message designs, which can backfire and offend users who may feel that the chatbot is downplaying the seriousness of their SRH questions.

Support, Trust and Reliability

Empathetic messages increased feelings of trust and support among participants as seen from how participants cited phrases such as “Let’s work together” indicating that they felt a sense of union and partnership. Participants who preferred the non-empathetic messages felt that the straightforward and factual tone would portray more credibility and trust. It was also important to note that this differing perspective did not reduce the participant’s willingness to engage with the chatbot. Instead, this structured and informational message design made one participant feel that the information provided by the chatbot was “more reliable” and reassured another participant as the chatbot “knew the answers”. A different participant indicated that he would use a chatbot when he needed “emergency information”. During such urgent times, “direct information would be appreciated.” This emphasizes that although there are benefits of using empathetic communication to foster self-disclosure and connectedness, the purpose and nature of the SRH chatbot should not be ignored. The purpose of SRH chatbots is to provide users with a credible, objective and neutral resource so that they can navigate different SRH challenges. Overly empathetic or friendly chatbot messages might steer away this purpose. While finding a one-size-fits-all solution may not be optimal, offering customizable communication styles may better suit the needs of diverse user preferences.

Comfort with Self-Disclosure

An important finding about self-disclosure was that it was largely dependent on the participant’s perception of the chatbot’s tone and how it made them feel during the interaction. Given the sensitive nature of SRH information, participants who preferred the empathetic message design mentioned that the “friendly” nature of the chatbot would set the mood for their interaction. This would made them feel “at ease” or “comfortable” to share more information about sensitive topics. This environment made participants feel that they would have a sustained

interest in conversing with the chatbot over time. However, participants who preferred the non-empathetic messages mentioned that they felt the chatbot did not seem to be “prying for information” as the messages were based on facts. This created a less intrusive space although it did not particularly increase their willingness or interest to interact with the chatbot for a prolonged time. One participant did mention that given the concise and professional approach of the non-empathetic message, she would predict sustained ongoing use as “it does not waste time and is to the point”.

Suggestions for Improvement

When asked for constructive feedback, participants emphasized the need to “find a middle ground”. While empathetic messages did foster a sense of support, guidance and care, excessive empathy could come across as “insincere” or “patronizing”. This could result in the opposite effect where users would reduce engagement with the chatbot. As one respondent put it, “The second one (empathetic message) can be less nice—there were too many emojis.” Additionally, the overuse of emojis could decrease the seriousness of sensitive SRH issues and downplay the gravity of its nature. Some participants also felt that the use of emojis sometimes had a “poking fun” or “mocking” connotation which was not helpful when discussing vulnerable SRH topics. Empathetic messages made the interaction “less sterile”, but these insights highlighted the importance of nuanced communication styles that blended both warmth, care, credibility and a sense of professionalism.

Discussion

The findings from this study provide valuable insights into how empathetic versus non-empathetic communication styles in chatbot messaging influence user engagement, perceptions, and self-disclosure, as outlined in the research questions.

Empathetic Messaging and Intentions to Self-Disclose (RQ1)

Findings suggest that empathetic messaging did play a part in enhancing participant's willingness to self-disclose and interact with the chatbot. This was especially true for participants who valued emotional support, guidance and reassurance when interacting with SRH chatbots. Conversational tone, the use of affirming messages and emojis were seen as important features that would encourage two-way and sustained conversations between user and chatbot. These human qualities felt as though participants were communicating with a trusted partner or friend, creating an environment where they would be more willing to disclose sensitive SRH information. Additionally, given the sensitive nature of SRH topics, these features enhance feelings of care and attentiveness towards SRH issues, making the participant feel a sense of value and importance. This in turn created space for potential deeper engagement.

However, there were participants who also felt that overly empathetic messages that steered away from neutral and factual tones decreased trust and willingness to engage with the chatbot. As the purpose of the SRH chatbot is not used for fun or entertainment, overly empathetic tones could evoke feelings of insincerity and discomfort. These mixed feedback shows how message design does impact users' willingness to self-disclose and engage with the chatbot. However, messages are a powerful feature that should be carefully calibrated to provide users with information in a warm and professional manner. The use of emojis could be included in moderation depending on the gravity of the information provided. This would show more emotional reliability and relevance while maintaining appropriate reactions to a given topic.

Human-Like Communication and Decision-Making (RQ2)

Human-like communication styles such as encouraging phrases and expressive tones were well-received. Many participants in this study were able to tell the difference between the

first and second message immediately by indicating that the second message (empathetic message) was more “human”. Participants also stated that these features did contribute to shaping their decisions to use the SRH chatbot as it fostered a sense of trust and relatability. This was similar to broader literature understanding anthropomorphism and the development of trust between humans and chatbots (Shumanov & Johnson, 2021; Chen et al., 2022).

There were some participants who felt that the overuse of human-like characteristics would make the experience distracting and advised that there should be a threshold considering the question “how much is too much”. Excessive use of human-like characteristics felt unnatural, manipulative and artificial, creating a sense of distrust and reducing willingness or interest to engage with the SRH chatbot. This duality underscores the importance of balancing human-like communication styles when developing a chatbot. While relatability can indicate more likeness and encourage engagement, too much of this element can undermine the credibility of the intervention. More testing needs to be done to identify an optimal communication style where human-like qualities can be implemented in a subtle and context-appropriate manner, striking the right balance.

Personalization and User Satisfaction (RQ3)

With more disclosure by the user, chatbots are able to offer more personalized and tailored information. Findings from this study showed that empathy stimulated self-disclosure which in turn increased perceived levels of user satisfaction. This finding also aligned with other studies that revealed how a chatbot’s emotional disclosure significantly increased user satisfaction and prolonged engagement, indicating positive effects of artificial emotions on disclosure (Park et al., 2022). Personalization of messages facilitated by empathetic messaging appeared to strengthen users’ trust and willingness to interact with a chatbot over time. Similarly,

participants who preferred the non-empathetic and straightforward messages appreciated the clarity and directness of the messages, appealing to their task-oriented nature.

Overall, this showed that personalization in chatbot messaging can take different forms, but ultimately, having tailored messages according to the users' needs, whether in an empathetic or non-empathetic form, enhances user satisfaction. This feature is important for the development of SRH chatbots because it supports a more inclusive and user-centered approach, acknowledging that users have different communication preferences. Developers can train chatbots to ask users about their preferred communication preferences during onboarding and create multiple message variants for each scenario. Machine learning models can be used to match responses with user profiles.

Insights on Messaging Designs and Implications for Trust (RQ4)

While users felt understood and heard through empathetic dialogues, there was emphasis on the purpose of an SRH chatbot, where factual and clear dialogues should be priority. The purpose of SRH chatbots is to be a digital concierge guiding users to relevant information and directing them to the appropriate services they might need. From this perspective, empathetic messages served to provide social support, but accurate information conveyed using a professional tone enhanced perception of trust. These findings suggest that trust can be fostered through both empathetic and non-empathetic messaging, albeit different pathways. Relational trust between humans and chatbots can be developed through empathetic messaging whereas cognitive trust can be developed through non-empathetic, neutral and factual messaging.

Balancing Emotional Engagement and Professionalism

Overall, an important takeaway from this study was the adaptability of chatbot in their messaging and communication style. There was not a better or worse message design but the

need for the appropriate communication style to encourage disclosure and willingness to engage with the SRH chatbot. There were multiple suggestions for the chatbot to be able to understand the users' communication preference and reciprocate it. There needed to be a balance between emotional and neutral tones, encouraging the development of a user-centric chatbot where communication styles are flexible and can be adjusted based on the user's interaction patterns. Addressing the research question, this study found that both empathetic and non-empathetic messages affected the users' willingness to self-disclose and engage with the chatbot. Empathy fostered trust but when overused, created a sense of insincerity. Users who required urgent SRH information or approached the chatbot from a task-oriented perspective preferred non-empathetic conversations with more information and options for additional signposting help. While human-qualities increased willingness to communicate with the chatbot to a certain extent, it has to be used in a balanced manner, maintaining the authenticity of the chatbot.

Ultimately, the findings underscore the importance of adaptability in chatbot messaging to meet the diverse needs of users, creating an inclusive and effective digital health tool. An area for future research is to differentiate the effects of tone and emojis in HMC. It remains unclear if the use of empathetic messages alone, without emojis' would have been an effective message design compared to the purely non-empathetic messages. To further test this, researchers can use a controlled experimental design and isolate these characteristics for deeper insights about linguistic and visual features.

Implications

The findings of this study carry several important implications for the design, development, and application of sexual and reproductive health chatbots, as well as digital health

tools more broadly. These implications span practical, theoretical, and ethical considerations, emphasizing the need for user-centered and adaptable chatbot design.

Practical Implications

A key takeaway from this study is to note that users have very different communication styles and preferences. There is no one-size-fits-all solution or “the best” chatbot message design. Instead, researchers and developers should place importance on the personalization of HMC. Chatbots should incorporate the ability to adapt to the users’ preferred communication style such as clarifying with the users during the onboarding stage about their preferred dialogue style or use adaptive algorithms to adjust the chatbot’s communication style to match the user’s communication patterns. This type of personalization can potentially increase user satisfaction, trust and overall engagement.

An additional critical insight is the duality of trust and how different types of trust can be fostered through messaging styles. Empathetic messages using affirming and warm tone can build relational trust whereas non empathetic messages with evidence-based and factual messages build cognitive trust. Researchers and developers in this area should find a balance as both types of messages can be effective based on the user’s preferences. Especially in SRH chatbots where information discussed or disclosed can be sensitive, and users need both emotional reassurance and factual accuracy, establishing the balance of both in message design is important.

While empathy is a critical tool to encourage self-disclosure, there should be a threshold where chatbots should not overuse this emotional element. Developers should include empathetic chatbot language in moderation or according to the users’ preferences. Trying too hard to mimic

human empathy will reduce trust and hinder engagement. Striking the right balance is the key towards ensuring that the SRH chatbot remains a supportive and credible resource.

These findings can be applied to broader digital health tools in the health space that could benefit from scalable personalization models and the use of adaptive communication strategies in HMC. Interdisciplinary collaboration and leveraging machine learning functions to examine interaction patterns and predict preferences could ensure that the resource can be adopted by a diverse community.

Ethical Implications

Transparency is critical and users should be aware and understand that they are interacting with an AI tool and not a human. Chatbots should also be developed using appropriate guardrails without providing bias or misleading information. When the chatbot cannot deliver the function requested, there should be a message to inform the user without manipulating or overpromising the outcomes. Maintaining the integrity of the digital tool will help to build trust and ensure that the ethical standards of HMC is uphold.

Theoretical Implications

From a theoretical perspective, these findings contribute to our understanding of self-disclosure and HMC. This study showed how communication styles can influence user behavior, highlighting the importance of considering message design as a variable when evaluating chatbot use intentions. The use of empathetic and non-empathetic messages not only influences communication styles and preferences but can also affect the level of disclosure and social or cognitive trust. Future research could explore more types of communication styles and preferences as well as the thresholds to which these features could enhance or reduce engagement. Expanding this study to different social and cultural groups can also offer unique

insights about how cultural norms or values could influence chatbot interaction ensuring that the chatbot is inclusive and responsive to the diverse needs of users.

There is a promising potential for health chatbots to advance health equity by providing a accessible and user-friendly resource to discuss sensitive health concerns. This judgment-free tool could reduce stigma and address care for members of marginalized populations. To achieve this goal, an inclusive design process is necessary to ensure that chatbots are competent and relevant.

Altogether, the findings emphasize the need for adaptive, user-centered, and ethically grounded chatbot design. By balancing empathy with professionalism and prioritizing personalization, chatbots can enhance user engagement, trust, and satisfaction while promoting equitable access to health information and support. These implications are crucial for leveraging digital health tools to improve individual and population health outcomes effectively.

CHAPTER 8

Conclusion

Optimize to Maximize

This dissertation began with the goal of studying how SRH chatbots could be optimized to maximize its promising potential. SRH chatbots are digital health interventions that can promote effective, inclusive and user-centered SRH management among young adults if they are designed with attention to users' needs, health motivations, technological usability and interpersonal dynamics such as fostering a trusting and engaging environment. In response to the gaps in literature on HMC, this study proposed and empirically tested an integrated theoretical framework combining the Health Belief Model, the Unified Theory of Acceptance and Use of Technology, and the Computers Are Social Actors paradigm. Using a multi-phase mixed-methods approach, the research investigated not only behavioral intentions and usability factors but also subgroup differences and the impact of empathetic message design on user trust and self-disclosure.

Insights from Quantitative Study

The quantitative phase of this study showed that the newly proposed integrated model offered a robust explanatory power in predicting intentions to use SRH chatbots. The model showed strong predictive validity, accounting for over 64% of the variance in behavioral intention. The results demonstrated that the framework provided a reliable and valid structure in understanding how young adult users were motivated to interact with SRH technology. Future studies can build on this integrated approach by testing among different populations, different health domains or different health technologies to explore its generalizability.

Among the general population, key variables such as self-efficacy emerged as a powerful predictor towards behavioral intentions to use SRH chatbots to manage one's SRH. The significance of self-efficacy was further strengthened by the finding that digital health literacy moderated its effect. This meant that when individuals had a high level of digital health literacy, either through education or awareness, they were more likely to have higher levels of confidence to navigate SRH chatbots and use it to manage their SRH. This highlighted a crucial consideration for both design and implementation: building confidence must go hand-in-hand with improving users' digital health competencies.

Interestingly, anthropomorphism had strong connections with the performance and effort expectancies (functionalities) of the SRH chatbot revealing important insights from the HMC perspective. HMC frameworks identify machines as active participants in interactions with humans and often assign human-like traits to these machines (Greussing et al., 2022). In this study, the chatbot's anthropomorphic features—such as a conversational tone, emotionally supportive language, or human-like phrasing—appeared to influence users' perceptions of the chatbot's capabilities, specifically its performance expectancy (how useful or effective it is) and effort expectancy (how easy it is to use). This finding suggests that digital health tools need to be considered not just in the task-oriented perspective but also in the social and relational lens. When chatbots feel more human-like, users may find them more intuitive, reducing the psychological distance between humans and machines.

The model also revealed that perceived benefits significantly predicted intentions to use SRH chatbots, further validating the idea that users are motivated by practical gains such as anonymity, accessibility, and empowerment. However, perceived barriers—traditionally expected to negatively influence intention—showed a small but positive and significant

relationship. This unexpected result may suggest that for some users, especially those aware of structural or interpersonal barriers in traditional care, such recognition actually motivates engagement with digital alternatives like chatbots. In this context, barriers do not deter action but instead serve as motivational cues, prompting users to seek more accessible, private, and stigma-free solutions.

Insights from LGBTQ+ Users

The subgroup analysis among LGBTQ+ individuals showed that values such as anonymity, inclusivity, empathy and a judgement-free supportive space was important when evaluating intentions to use chatbots to manage SRH. Similar to the general population, digital health literacy was a significant moderator in amplifying the relationship between self-efficacy and behavioral intentions. This alluded to the fact that education and awareness about digital health literacy was crucial. A unique difference between the LGBTQ+ population and the general population was social influence. Social influence describes the extent to which individuals perceive how important others (e.g., friends, family, or healthcare providers) think they should use technology (Venkatesh et al, 2012).

Unlike the general population, social influence was less significant to LGBTQ+ individuals indicating that this group of users relied less on external endorsements to decide whether they should use SRH chatbots. Rather than being influenced by the opinions of others, LGBTQ+ individuals prioritized their own needs when making such decisions. This finding suggested that LGBTQ+ users took a more cautious and independent approach when seeking SRH resources, possibly shaped by lived experiences of stigma, discrimination or lack of trust in traditional care. The social context of digital health adoption varies widely across different communities, highlighting the importance of paying closer attention to unique identity-based

needs, lived experiences and structural barriers influencing how different populations navigate health technology.

Insights from Qualitative Study

The qualitative phase of the study provided rich insights on how users perceive different chatbot communication styles, highlighting that there was no “one-size-fits-all” communication style. While participants appreciated the emotional validation, warmth and support from the use of emojis and empathetic tones as they provided psychological safety and trust, there was a threshold which should not be crossed. Too much empathy and human-likeness created a sense of insincerity and decreased willingness to interact with the chatbot. This reinforced the importance of designing chatbot responses that feel supportive without straying into artificial mimicry of human emotion. Additionally, participants highlighted a desire for autonomy and customization in the conversation flow—emphasizing the importance of allowing users to control the direction of the interaction. A scalable and implementable recommendation would be to incorporate communication style options during the onboarding process. This will allow users to select their preferred communication style, fostering a more tailored and personalized user experience.

Theoretical and Practical Contributions

This dissertation offers several important contributions to both theory and practice in the fields of health communication, human-machine interaction, and digital health design.

Theoretically, the integration of the Health Belief Model, the Unified Theory of Acceptance and Use of Technology, and the Computers Are Social Actors framework presents a novel, multidimensional approach to understanding user behavior in digital health contexts. By combining health behavior motivations, usability and performance perceptions, and socially

interactive elements, this integrated model advances theory-building in human-machine communication. This research also contributes to the growing interest in equity and user-centered design in digital health interventions, intentionally highlighting the importance of inclusive approaches. Additionally, findings expand on the literature about HMC and communication style when interacting with chatbots. Illustrating the dual role of empathetic messages as both a facilitator of trust and discomfort if exceeding a threshold. The study provides valuable guidance for balancing emotional resonance with authenticity in chatbot communication.

As for design recommendations, which is an important aspect in contributing to chatbot engagement, clear and intuitive design features are essential to increasing self-efficacy. User autonomy through personalization options allowing for flexible conversation flows and customizable paths should be considered and implemented. Cultural competence and inclusivity should be embedded throughout the chatbot's content and interaction logic. Lastly, it is key to strengthening digital health literacy through onboarding prompts that explain how the chatbot works, reassurances about data privacy, and embedded educational content. These elements can empower users who may be less familiar with digital health tools and increase their confidence and willingness to engage.

Limitations

There were several limitations in this dissertation. Although the quantitative section utilized a large and diverse national sample, it was not a longitudinal study. Hence, actual behavior change could not be observed. The use of a single publicly available chatbot may also have constrained generalizability as findings may not fully extend to other chatbots with different features. Constructs that were removed from the integrated model could be included in

subsequent studies to test its adaptability and relationships with intentions. The qualitative component, while rich in interpretive depth, was limited to self-selected participants who may already hold favorable attitudes toward chatbots, potentially introducing selection bias. While digital health literacy was examined as a moderator, future studies could benefit from a more granular exploration of intersectional factors such as socioeconomic status, race and ethnicity, and geographic access to care, which may also shape user engagement with SRH chatbots.

Future Directions

Future studies in this area should consider longitudinal research studies to understand the sustained impact of using SRH chatbot and empirically test behavior change. This would help determine not only short-term engagement but also whether chatbots influence longer-term decision-making, health outcomes, or service-seeking behaviors. Cross-cultural and multilingual studies exploring SRH chatbots on a global scale through an international lens could inform the development of more inclusive, adaptable and culturally responsive health technologies. Lastly, there is a growing need for organized and structured policy and ethical frameworks to govern the use of AI technology used in health interventions. These frameworks should prioritize data transparency, stricter guardrails, confidentiality, informed consent, and equitable access. As chatbots become more widely used in healthcare settings, researchers and practitioners must work with policymakers to establish trust-based standards for safe and responsible use.

In an era where digital technologies are quickly shaping the way we access, understand and manage our healthcare, it is important to establish a roadmap for inclusive health interventions that are grounded in real-world user needs. SRH is an area of health that is sensitive and can make a person feel vulnerable. Thoughtfully and ethically developed interventions can serve as trusted companions providing users with a sense of agency and

support often lacking in traditional healthcare systems. While SRH chatbots are not meant to replace traditional healthcare, it is a complementary tool that enhances access and empowers users, especially those who face stigma in this space.

This dissertation serves as a theoretical contribution and a practical call to action on how SRH chatbots can be optimized to maximize their promising potential. As the intersection of AI, digital interventions and healthcare evolves, it is important that our society creates not just innovative solutions but also compassionate and equitable interventions, respecting the complexity of the human experience while ensuring that users feel supported in their health journey.

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Appendix A

Qualitative Survey Questionnaire

Survey Questions for RQ1: Empathetic vs. Non-Empathetic Communication

1. Can you describe your feelings when interacting with chatbot messages that seemed empathetic? How did these feelings influence your willingness to share personal information?
 2. How did messages that felt less empathetic (or neutral) affect your decision to engage further with the chatbot?
 3. What specific aspects of a chatbot's messaging make you feel more comfortable sharing sensitive information?
-

Survey Questions for RQ2: Human-Like Communication Perceptions

4. When the chatbot communicated in a way that seemed human-like, how did this affect your perception of its reliability and trustworthiness?
 5. Can you share any specific experiences where the chatbot felt more or less "human"? How did this influence your engagement?
 6. What aspects of the chatbot's communication style (e.g., tone, word choice, response speed) made it feel more like interacting with a person rather than a machine?
-

Survey Questions for RQ3: Self-Disclosure and Personalized Responses

7. How did the chatbot's ability to provide personalized responses after you shared personal information affect your overall satisfaction with the interaction?
 8. What specific examples of personalized responses made you feel that the chatbot understood your needs?
 9. If you hesitated to share certain information, what could the chatbot have done to make you feel more comfortable disclosing?
-

Survey Questions for RQ4: Effectiveness of Empathetic and Non-Empathetic Messages

10. What did you find most effective about the empathetic messages in terms of building trust and encouraging interaction?
11. In what ways did non-empathetic messages fall short of your expectations, if at all?
12. How would you compare your trust levels and engagement with the chatbot when interacting with empathetic versus non-empathetic messages?
13. Based on your experience, what suggestions do you have for improving chatbot communication to foster trust and encourage greater use?

Appendix B

Demographic Table

Demographic Characteristics of Sample

Variable	N	%	M	SD
Age				
18-24	168	14.000		
25-32	1032	34.200		
Gender				
Man	429	35.800		
Woman	719	59.900		
Transgender Man	10	0.800		
Transgender Woman	4	0.300		
Nonbinary	25	2.100		
Genderqueer	2	0.200		
Genderfluid	8	0.700		
Prefer not to say	1	0.100		
Other (Agender)	1	0.100		
Other (Demigender)	1	0.100		
Sexual Orientation				
Heterosexual	845	70.400		
Homosexual	70	5.800		
Bisexual	189	15.800		

Pansexual	36	3.000
Asexual	22	1.800
Questioning	14	1.200
Prefer not to say	18	1.500
Other (Nonbinary)	1	0.100
Other (Omnisexual)	1	0.100
Other (Queer)	3	0.300

Race

White	767	63.900
Black/African American	325	27.100
Asian	97	8.100
Native Hawaiian or Other Pacific Islander	17	1.400
American Indian or Alaskan Native	37	3.100
Prefer not to say	11	0.900
Other	45	3.800
Hispanic, Latino, or Spanish	240	20.000

Highest Level of Education

3.470 1.400

Some high school	32	2.700
High school diploma	374	31.200
Some college	258	21.500

Associate degree	142	11.800
Bachelor's degree	309	25.800
Graduate degree	81	6.800
Other	4	0.300

Marital Status

Single	684	57.000
Married	226	18.800
In a relationship	263	21.900
Divorced	19	1.600
Widowed	4	0.300
Prefer not to say	4	0.300

Employment Status

Employed full-time	635	52.900
Employed part-time	206	17.200
Unemployed	192	16.000
Student	131	10.900
Retired	1	0.100
Other	35	2.900

Residing State

Alabama	14	1.200
Alaska	1	0.100
Arizona	31	2.600

Arkansas	22	1.800
California	123	10.300
Colorado	13	1.100
Connecticut	8	0.700
Delaware	3	0.300
Florida	85	7.100
Georgia	51	4.300
Hawaii	3	0.300
Idaho	6	0.500
Illinois	47	3.900
Indiana	28	2.300
Iowa	9	0.800
Kansas	11	0.900
Kentucky	28	2.300
Louisiana	17	1.400
Maine	3	0.300
Maryland	27	2.300
Massachusetts	20	1.700
Michigan	37	3.100
Minnesota	19	1.600
Mississippi	6	0.500
Missouri	29	2.400

Montana	7	0.600
Nebraska	4	0.300
Nevada	10	0.800
New Hampshire	3	0.300
New Jersey	24	2.000
New Mexico	8	0.700
New York	93	7.800
North Carolina	48	4.000
North Dakota	2	0.200
Ohio	46	3.800
Oklahoma	18	1.500
Oregon	11	0.900
Pennsylvania	58	4.800
Rhode Island	2	0.200
South Carolina	19	1.600
South Dakota	2	0.200
Tennessee	31	2.600
Texas	97	8.100
Utah	2	0.200
Vermont	1	0.100
Virginia	26	2.200
Washington	19	1.600

West Virginia	8	0.700
Wisconsin	20	1.700
Wyoming	1200	100.000

Type of Residential

Area

City (Urban)	457	38.100
Town (Suburban)	582	48.500
Countryside (Rural)	158	13.200
I don't know	3	0.300

Household Income

3.380 1.679

Below \$20,000	169	14.083
\$20,000-\$39,999	255	21.250
\$40,000-\$59,999	270	22.500
\$60,000-\$79,999	192	16.000
\$80,000-\$99,999	118	9.833
\$100,000 and above	169	14.083
Prefer not to say	27	2.250

Appendix C

Measurement Items and Reliability Check

Measurement Items and Reliability Check

Attribute	Variable	Item	M	SD	Cronbach's α
Health (HBM)	Perceived Benefits	1. Using a sexual and reproductive health chatbot will help me find sexual and reproductive information.	4.950	1.599	.869
	Benefit_1				
Health (HBM)	Perceived Benefits	2. Using a sexual and reproductive health chatbot will improve my sexual and reproductive health knowledge.	5.210	1.527	
	Benefit_2				
Health (HBM)	Perceived Benefits	3. Using a sexual and reproductive health chatbot will improve my overall sexual and reproductive health management.	5.030	1.553	
	Benefit_3				
Health (HBM)	Perceived Barriers	1. Using a sexual and reproductive health chatbot is time-consuming.	4.100	1.893	.720
	Barrier_1				
Health (HBM)	Perceived Barriers	2. I do not have access to a sexual and reproductive health chatbot.	3.340	1.789	
	Barrier_2				

Health (HBM)	Perceived Barriers	3. I do not know how to use a sexual and reproductive health chatbot.	3.040	1.881	
	Barrier_3				
Health (HBM)	Self-efficacy	1. I can see myself using a sexual and reproductive health chatbot.	4.960	1.657	.849
	Efficacy_1				
Health (HBM)	Self-efficacy	2. I feel more empowered about my health when I use a sexual and reproductive health chatbot.	4.770	1.622	
	Efficacy_2				
Health (HBM)	Self-efficacy	3. I feel confident in using information from a sexual and reproductive chatbot to make health	5.210	1.574	
	Efficacy_3				
Functional (UTAUT)	Performance Expectancy	1. The information provided by a sexual and reproductive health chatbot helps me to understand my health better.	4.83	1.636	.796
	Perf_1				
Functional (UTAUT)	Performance Expectancy	2. A sexual and reproductive chatbot can help me manage my sexual and	5.14	1.524	
	Perf_2				

		reproductive health.			
Functional (UTAUT)	Performance Expectancy	3. I feel reassured that a sexual and reproductive health chatbot can effectively address my health concerns.	5.12	1.493	
	Perf_3				
Functional (UTAUT)	Effort Expectancy	1. Using a sexual and reproductive health chatbot is easy for me.	5.410	1.472	.918
	Effort_1				
Functional (UTAUT)	Effort Expectancy	2. It is simple for me to learn how to use a sexual and reproductive health chatbot.	5.430	1.508	
	Effort_2				
Functional (UTAUT)	Effort Expectancy	3. Operating a sexual and reproductive health chatbot is easy for me.	5.500	1.492	
	Effort_3				
Functional (UTAUT)	Social Influence	1. I will use a sexual and reproductive health chatbot if people important to me approve of its use.	4.690	1.655	.854
	Soc_1				
Functional (UTAUT)	Social Influence	2. I will use a sexual and reproductive health chatbot if the community around me supports it.	4.640	1.683	
	Soc_2				
Functional (UTAUT)	Social Influence	3. I will use a sexual and reproductive	5.160	1.598	

	Soc_3	health chatbot if my trusted doctor/health provider introduces it to me.			
Interactive (CASA)	Autonomy	4. I am more likely to use a sexual and reproductive chatbot when it follows my lead instead of trying to steer the discussion to its agenda.	5.350	1.568	
	Anthro_4				
Moderator	e-health Literacy	1. I know what health resources are available on a sexual and reproductive chatbot.	4.940	1.550	.932
	Literacy_1				
Moderator	e-health Literacy	2. I know where to find helpful health resources on a sexual and reproductive chatbot.	5.060	1.502	
	Literacy_2				
Moderator	e-health Literacy	3. I know how to find helpful health resources on a sexual and reproductive chatbot	5.160	1.485	
	Literacy_3				
Moderator	e-health Literacy	4. I know how to use a sexual and reproductive chatbot to answer my questions about health.	5.320	1.487	
	Literacy_4				

Moderator	e-health Literacy Literacy_5	5. I know how to use the health information I find on a sexual and reproductive chatbot to help me.	5.300	1.421	
Moderator	e-health Literacy Literacy_6	6. I have the skills I need to evaluate the health resources I find on a sexual and reproductive chatbot	5.330	1.425	
Moderator	e-health Literacy Literacy_7	7. I can tell high-quality health resources from low-quality health resources on a sexual and reproductive chatbot.	5.200	1.493	
Outcome	Intention_1	1. I will use a sexual and reproductive chatbot to manage my sexual health.	4.840	1.699	.901
Outcome	Intention_2	2. I will use a sexual and reproductive chatbot to make my sexual and reproductive health appointments.	4.560	1.754	
Outcome	Intention_3	3. I plan to frequently use a sexual and reproductive health chatbot to make my overall sexual and reproductive health decisions.	4.630	1.802	

Literacy_7			0.778
Perf_1		0.723	
Perf_2		0.908	
Perf_3		0.900	
Soc_1			0.902
Soc_2			0.906
Soc_3			0.829
e-Lit x			
Efficacy			1.000

Appendix E

Multicollinearity Statistics (VIF) for Indicators

Multicollinearity Statistics (VIF) for Indicators

	VIF
Barrier_1	1.191
Barrier_2	2.106
Barrier_3	2.211
Benefit_1	2.083
Benefit_2	2.570
Benefit_3	2.342
Efficacy_1	2.392
Efficacy_2	2.682
Efficacy_3	1.724
Effort_1	3.041
Effort_2	3.754
Effort_3	3.244
Human_1	1.950
Human_2	3.129
Human_3	2.901
Human_4	2.327
Intention_1	2.772
Intention_2	2.612
Intention_3	3.304

Literacy_1	2.873
Literacy_2	4.119
Literacy_3	3.999
Literacy_4	2.992
Literacy_5	2.979
Literacy_6	2.998
Literacy_7	2.205
Perf_1	1.328
Perf_2	2.692
Perf_3	2.614
Soc_1	2.492
Soc_2	2.554
Soc_3	1.753
e-Lit x Efficacy	1.000
