NOVA IMS
Information Management School

MGI

Master Degree Program in

Information Management

Exploring User Acceptance of AI Chatbots in Mental Health Support

Martim Marques Mendes

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Information Management

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

Exploring User Acceptance of AI Chatbots in Mental Health Support

by

Martim Marques Mendes

Master Thesis presented as partial requirement for obtaining the Master's degree in Information Management, with a specialization in Business Intelligence

Supervised by

Mijail Naranjo Zolotov, PhD, NOVA Information Management School

July, 2025

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisbon, 14th of July 2025

Martim Marques Mendes

DEDICATION

For my parents -

your quiet sacrifices, unwavering love and support have carried me to where I stand today. Each step of the journey has been built on the foundation you gave me. I truly am grateful for everything you have done for me.

ACKNOWLEDGEMENTS

I would like to extend my heartfelt thanks to the professors and staff at NOVA IMS, whose dedication, support, and professionalism have made this journey not only possible but truly gratifying. NOVA IMS has been a second home to me since 2019, and it will always hold a very special place in my heart.

A very special thank you to my supervisor, professor Mijail Naranjo, for his constant availability, clear guidance, and kind approach throughout this process. Your support made all the difference.

To all those who participated in the data collection phase, thank you for contributing your time and insights.

To my friends, who throughout the past year have consistently supported me and encouraged me to keep working and finishing this thesis, I am truly grateful for each and every one of you. I won't name names, not only because I'd hate myself for forgetting someone, but also because I know you'd never let me live it down (and rightfully so). You know who you are.

Finally, I would like to express my gratitude to my family for their unwavering love and support during my journey. You have been a constant source of support and encouragement throughout my life, both my personal family and my cousins. I cannot put into words how much I valued the time we spent together, especially the lengthy video calls that were full of encouragement and humour. You reminded me of what really mattered and made me feel close, even from afar. Without you, I genuinely wouldn't be where I am now. Thank you from the bottom of my heart.

ABSTRACT

The global rise in mental health disorders has placed growing pressure on traditional diagnostic and therapeutic systems, often leaving individuals without timely or adequate care. AI-powered chatbots offer a promising alternative by delivering scalable and accessible mental health support. However, concerns about trust, privacy, algorithmic bias, and ethical responsibility continue to limit their adoption. This study explores how psychological and technological factors including trust, perceived usefulness, privacy concerns, and mental health stigma influence user acceptance of AI chatbots in mental healthcare. The analysis is guided by a combined theoretical framework that integrates the Technology Acceptance Model, the Health Belief Model, the Trust in Technology Framework, and the Unified Theory of Acceptance and Use of Technology. Using Structural Equation Modelling, the study tests relationships among key constructs that shape user attitudes and behavioural intentions. Findings show that trust and perceived competence strongly predict intention to use, while privacy concerns and stigma present major barriers. These insights inform ethical and user-centred AI design for mental health applications.

KEYWORDS

AI Chatbots; Mental Health; Technology Acceptance; Trust in Technology; Privacy Concerns

Sustainable Development Goals (SDG):

3 GOOD HEALTH AND WELL-BEING

TABLE OF CONTENTS

Statement of Integrity....i
Dedication....ii
Acknowledgements....iii
Abstract....iv
List of Figures....vii
List of Tables....viii
List of Abbreviations and Acronyms....ix
1. Introduction....1
1.1 Background and Relevance....1
1.2. Research Gap....1
1.3. Research Question....2
1.4. Study Contributions....3
2. Literature Review....4
2.1. Hypotheses Development....4
2.1.1. Technology Acceptance Model (TAM)....4
2.1.2. Trust in Technology Framework....5
2.1.3. Health Belief Model (HBM): The Moderating Role of Stigma....5
2.1.4. Unified Theory of Acceptance and Use of Technology (UTAUT)....6
2.2. Literature Support for Hypotheses....6
2.2.1. Facilitating Conditions and Ease of Use....6
2.2.2. Perceived Usefulness and Engagement....7
2.2.3. Trust as a Mediator....8
2.2.4. Social Influence and Endorsement Effects....8
2.2.5. Privacy Concerns as a Barrier....9
2.3. Conceptual Framework....10
3. Methodology....11
3.1. Participants and Sampling....11
3.2. Procedure and Measures....11
3.3. Hypotheses....12
3.4. Data Analysis Strategy....12

4. Empirical Study 14
4.1. Data Preparation and Screening 14
4.2. Descriptive Statistics 14
4.3. Reliability and Validity of Constructs..17
5. Results and Discussion 19
5.1. Model Fit Assessment 19
5.2. Structural Model and Hypothesis Testing 20
5.3. Discussion of Key Findings 21
5.4. Theoretical Implications...23
5.5. Practical Implications 23
6. Conclusions and Future Research 25
6.1. Conclusion 25
6.2. Limitations and Directions for Future Research 25
Bibliographical References...27
Appendix A..35
Appendix B..36
Appendix C..42

LIST OF FIGURES

Figure 2.1 - Conceptual Framework of AI Chatbot Adoption for Mental Health Support 10
Figure 4.1 - Gender Distribution 15
Figure 4 2 - Age Distribution 15
Figure 4.3 - Educational Attainment 16
Figure A.1 - Ethics Committee Report.. 35
Algorithm B1 - Specification of the Measurement and Structural Model in R 41

LIST OF TABLES

Table 4.1- Means and Standard Deviations of the Latent Constructs 16
Table 4.2 - Reliability and Validity Metrics for Each Construct 17
Table 5.1 - Model Fit, Indices and Thresholds 19
Table 5.2 - Hypothesis Testing Results: Coefficients, Estimates and Support Outcomes 20
Table B1 - Construct's Skewness and Kurtosis Values 36
Table B2 - Variance Inflation Factor (VIF) Table 37
Table B3 - Full AVE Matrix (Fornell-Larcker Criterion) 38
Table B4 - HTMT Matrix 38
Table B5 - SEM - Standardised Loadings 39
Table B6 - SEM Output - Covariances, Intercepts and Residual Variances 40

LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence. Refers to computer systems capable of performing tasks that typically require human intelligence, such as language processing or decision-making.
AVE	Average Variance Extracted. A metric for evaluating convergent validity in structural equation modelling, reflecting the amount of variance captured by a construct relative to measurement error.
CFA	Confirmatory Factor Analysis. A technique within structural equation modelling used to validate measurement models by confirming whether observed data fit a hypothesized factor structure.
CFI	Comparative Fit Index. An incremental fit index used in structural equation modelling to compare the fit of a user-specified model to a baseline model.
COMP	Perceived Competence of AI. Measures the extent to which users believe AI systems can deliver intelligent, accurate, and emotionally appropriate responses.
CR	Composite Reliability. A measure of internal consistency used in structural modelling to assess the reliability of latent constructs.
FC	Facilitating Conditions. Reflects the user's perception of the resources and support available to use the technology effectively.
HBM	Health Belief Model. A behavioural health framework used to explain individual decisions regarding health interventions, considering perceived severity, benefits, and barriers.
IU	Intention to Use. The likelihood or willingness of a user to engage with AI chatbots in future mental health scenarios.
ML	Machine Learning. A subset of AI that enables systems to improve performance by learning from data. Used in chatbot functionality for pattern recognition and adaptive support in mental health interventions.
NLP	Natural Language Processing. A field of AI focused on the interaction between computers and human language. It enables chatbots to interpret and generate human-like responses.
PC	Privacy Concerns. Reflects user apprehension about how personal data is collected, stored, and used by AI systems.
PEOU	Perceived Ease of Use. A construct from the Technology Acceptance Model assessing how effortless a user perceives a system to be.

PU Perceived Usefulness. A construct from the Technology Acceptance Model measuring the degree to which a user believes a system enhances their performance or outcomes.

R^2 Coefficient of Determination. Indicates the proportion of variance explained by predictors in a regression or structural model.

RMSEA Root Mean Square Error of Approximation. A fit index in structural equation modelling assessing how well a model fits the population covariance matrix.

SEM Structural Equation Modelling. A statistical method used to analyse complex relationships among variables, allowing simultaneous examination of direct, mediating, and moderating effects.

SI Social Influence. The degree to which individuals perceive that important others believe they should use a particular technology.

SRMR Standardised Root Mean Square Residual. A model fit index in structural equation modelling representing the standardised difference between observed and predicted correlations.

STIG Mental Health Stigma. Captures internalized or societal shame and judgment associated with seeking mental health support.

TAM Technology Acceptance Model. A theoretical framework that explains user acceptance of technology based on perceived usefulness and perceived ease of use.

TLI Tucker-Lewis Index. A goodness-of-fit index in structural equation modelling, adjusted for model complexity, used to evaluate model fit.

TR Trust in AI. Represents the user's belief in the reliability, transparency, and ethical behaviour of AI systems.

UTAUT Unified Theory of Acceptance and Use of Technology. A framework that integrates several technology acceptance models, emphasizing factors such as social influence and facilitating conditions.

VIF Variance Inflation Factor. A diagnostic measure used to detect multicollinearity among predictor variables in regression and structural models.

1. INTRODUCTION

1.1 BACKGROUND AND RELEVANCE

The prevalence of mental health conditions such as depression, anxiety, and mood disorders is rising worldwide, putting more pressure on healthcare systems and revealing gaps in quick and easily accessible treatment (Eskandar, 2024). Due to logistical challenges, stigma, and a lack of clinicians, traditional therapeutic approaches frequently fail, particularly in underprivileged populations.

Chatbots driven by AI have become scalable instruments, capable of offering behavioural triage, support, and preliminary assessments through automated conversation systems (Wester et al., 2024). These systems provide continuous interaction with low resource requirements by utilising machine learning (ML) and natural language processing (NLP) (Omiyefa, 2025). Despite their potential, the adoption of AI chatbots in mental healthcare is hindered by significant concerns, including trust, privacy, ethical risks, and algorithmic bias (Meadi et al., 2025).

Diagnostic errors may result from models trained on non-representative datasets failing to identify culturally specific symptom expressions (Yeasmin et al., 2025). Furthermore, when sensitive psychological disclosures are involved, a lack of transparency in AI decision-making can erode user confidence. Therefore, it is imperative to better understand user perceptions and concerns about AI-based mental health support.

1.2. RESEARCH GAP

Much of the existing research emphasizes the diagnostic performance of AI using techniques like emotion recognition or NLP, often overlooking contextual concerns notably stigma and explainability (Straw & Callison-Burch, 2020), as a result, there is comparatively little attention to psychological and ethical barriers and how it may hinder user adoption. Despite playing a crucial role in influencing the adoption of AI-driven tools, issues with trust, privacy, and stigma around mental health are still poorly understood. Walsh et al. (2020) point out that the clinical applicability of AI systems in behavioural health is limited when these human-centred aspects are ignored, especially algorithmic transparency and stigma. Our comprehension of how actual users evaluate AI-based mental health tools beyond their technical capabilities is limited by this oversight.

A key research gap concerns algorithmic bias, particularly the consequences of training AI systems on non-representative datasets. Many existing models lack demographic diversity in their training data, underrepresenting racial minorities, gender-diverse individuals, and those from lower socioeconomic backgrounds. This lack of inclusivity may lead to skewed diagnostic outputs, which can reinforce systemic biases and widen existing mental health disparities.

Biased assessments not only reduce the reliability of AI recommendations but also risk alienating users who already experience marginalization in traditional care settings (Timmons et al., 2023).

The adoption of AI-powered tools in mental health care frequently depends on how users view ethical responsibility, data security, and transparency. Research indicates that when users are unaware of the methods used to gather, store, or distribute data, they are less likely to divulge private psychological information (Meadi et al., 2025). A sense of surveillance and fear of misuse can result from opaque or inaccessible data usage policies coupled with a lack of transparency in algorithmic decision-making. This is particularly troubling in emotionally sensitive situations where moral limits need to be spelt out and strictly adhered to. Ethical chatbot design and perceived control over data flow play a crucial role in fostering trust and promoting user engagement in mental health contexts (F. Chen et al., 2025).

Another obstacle to the use of AI-based support tools is the stigma associated with mental illness. When seeking mental health services, people frequently encounter social judgement or internalised shame, despite increased awareness and continuous efforts to de-stigmatize the issue. This stigma may also apply to AI-powered platforms, where some users may link digital mental health tools to personal inadequacy or view them as less reliable than traditional therapy. However, by making help-seeking behaviour less visible, AI chatbots' anonymity and accessibility may lessen stigma for some groups (L. Li et al., 2024). Even so, perceived judgement, whether it be automated or human, can deter participation. Developing AI tools that are not only technically sound but also inclusive and psychologically acceptable requires an understanding of how stigma influences user behaviour (Dergaa et al., 2023).

These gaps highlight the need to move beyond evaluating what AI *can do* toward understanding whether and why individuals are willing to adopt these technologies. This study responds to that need by examining the intersection of psychological, ethical, and technological factors that influence the adoption of AI chatbots in mental healthcare. It is guided by an integrative framework drawing on the Technology Acceptance Model (TAM), the Trust in Technology Framework, the Health Belief Model (HBM), and the Unified Theory of Acceptance and Use of Technology (UTAUT).

1.3. RESEARCH QUESTION

This study investigates how psychological and technological perceptions influence the adoption of AI-driven chatbots in mental healthcare settings. Moving beyond narrowly focused perspectives that treat user behaviour and system design as separate concerns, the research applies an integrative framework to examine how trust, privacy concerns, mental health stigma, and perceived technological capability collectively shape user willingness to engage with these tools.

How do psychological factors such as trust, privacy concerns, and mental health stigma influence the adoption of AI-driven chatbots for mental health support?

This research question enables a multidimensional analysis that incorporates both user-side attitudes and system-level considerations. Guided by theoretical models including the Technology Acceptance Model (TAM), the Health Belief Model (HBM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Trust in Technology Framework, the study identifies core adoption drivers and inhibitors. In doing so, it contributes insights that support the development of more ethically aligned, user-centred AI interventions in mental health, with implications for both technological design considerations and strategies for public engagement.

1.4. STUDY CONTRIBUTIONS

This research integrates theoretical perspectives from established technology acceptance and behavioural health models to provide a nuanced understanding of the psychological and technological factors affecting the adoption of AI-driven chatbots in mental healthcare. The study utilises empirical data concerning constructs like trust, privacy concerns, stigma, perceived usefulness, and intention to use, offering significant contributions to academic literature and practical application.

First, by showing how user concerns about algorithmic bias and data privacy can influence engagement, it aids in the creation of ethical deployment strategies. These observations can help shape policies that place a high value on openness, diversity, and ethical data handling.

Second, the results aid mental health practitioners to understand the circumstances in which chatbots can be used as supplementary tools to increase access without undermining the role of human clinicians.

Finally, by examining the significant but frequently neglected psychological factors of stigma and trust in the context of AI-based mental health support, this study enriches current models of technology adoption.

2. LITERATURE REVIEW

2.1. Hypotheses Development

Four well-established theoretical frameworks are applied in this study to explain the technological and psychological aspects that affect users' adoption of AI chatbots in mental healthcare. These comprise of the Unified Theory of Acceptance and Use of Technology (UTAUT), the Health Belief Model (HBM), the Trust in Technology Framework, and the Technology Acceptance Model (TAM). Every framework offers a unique perspective on how people develop opinions about technology, assess perceived risks, react to social cues, and get past psychological obstacles such as stigma. When combined, these models provide a more thorough understanding of the adoption process, particularly in delicate areas where functional, ethical, and emotional aspects interact. (Jin et al., 2025; Mathew et al., 2024)

The conceptual model proposed in this study is informed by the strengths and complementarities of these frameworks. TAM highlights utility and usability as important adoption factors (Wu et al., 2025). Even in cases where technical features are satisfactory, HBM introduces individual psychological factors like stigma that can hinder engagement. Beliefs about data security, transparency, and dependability are the focus of the Trust in Technology Framework. UTAUT offers insights into how contextual support and social influence mould behavioural intentions (L. Li et al., 2024). Collectively, these viewpoints guide the structural relationships, including direct, mediating, and moderating effects which are tested in the model and inform the study's hypotheses.

2.1.1. Technology Acceptance Model (TAM)

According to the model, users' attitudes towards a system are shaped by two fundamental beliefs: perceived usefulness and perceived ease of use. These beliefs then have an impact on the users' behavioural intentions. Perceived ease of use reflects the expectation that the system will be effortless, whereas perceived usefulness refers to the conviction that utilising a specific technology will enhance task performance. This is supported by foundational work introduced by Davis (1989), as well as more recent empirical findings by Kelly et al. (2022), both of which affirm the ongoing relevance of perceived usefulness and ease of use in the context of AI-driven mental health chatbots.

These concepts are still particularly pertinent when discussing chatbots for mental health. Users may believe that a chatbot is more effective at meeting psychological needs if it is simple to use. For instance, users are more likely to perceive the tool as capable and reliable when interactions with the chatbot are seamless and responses are understandable. These impressions may strengthen trust in the system's dependability and have a direct impact on intention to use. This is consistent with research by Pang et al. (2024), who demonstrated through an extended TAM model that trust and adoption of health-diagnostic AI chatbots were significantly predicted by perceptions of usefulness and ease of use.

TAM by itself, however, might not be enough to comprehend how technology is used in emotionally delicate situations such as mental health treatment. Affective, ethical, and social factors that could affect user acceptance are not fully taken into consideration, despite its primary focus on functionality and usability. The current study integrates additional theoretical frameworks that consider psychological barriers, notably stigma, worries about data privacy, and the significance of interpersonal trust to address these limitations.

2.1.2. Trust in Technology Framework

People's willingness to use emerging technologies is greatly influenced by their level of trust, especially in delicate areas such as mental health care. According to McKnight et al. (2002), the Trust in Technology Framework describes several factors that affect users' perceptions of a technological system's reliability. These include trust in the system's ability to handle sensitive data and decision-making procedures, as well as opinions about its competence, integrity, and predictability.

Trust in AI-powered chatbots for mental health is closely tied to the system's transparency, consistency, and data handling practices. Users are more inclined to interact with a system when they believe it provides accurate responses, operates fairly, and safeguards personal data. User trust can be seriously damaged by worries about algorithmic bias, ambiguous reasoning, or imprecise privacy protections, particularly in emotionally delicate circumstances. These risks are increased in situations where users are disclosing sensitive information, such as mental health. According to recent research, justified trust is based on whether the AI system reflects the values and expectations of the user as well as perceived technical proficiency. (Manzini et al., 2024)

In addition to technical reliability, clear communication of data policies and ethical safeguards are essential for establishing and preserving trust in AI tools. This study models trust as a key construct that mediates the relationship between user intention to use AI-based mental health support and perceived system attributes. By adding trust as a separate component, the model recognises that user acceptance is based on both a tool's functionality and its compatibility with users' expectations of moral and responsible technology use.

2.1.3. Health Belief Model (HBM): The Moderating Role of Stigma

The Health Belief Model (HBM) is a psychological framework that looks at people's beliefs about illness, perceived risks, and obstacles to action in order to explain health-related behaviours. It draws attention to the ways that behaviour can be influenced by perceptions of severity, the advantages of acting, and perceived barriers, such as internalised stigma or mistrust of non-human interventions (Zhang et al., 2025). Fears of being judged by others or not knowing how to use AI tools can also be major deterrents in digital mental health settings.

The stigma attached to mental illness is a major barrier to the adoption of AI-driven support tools. Given that they believe a chatbot is less trustworthy than a human therapist or because they fear it shows weakness, users may be hesitant to use one for support. Even in cases where the technology is viewed as practical and user-friendly, stigma can cause social discomfort or feelings of embarrassment that impede behavioural intention. This is especially important for populations where digital interventions are less common or mental health is not well-discussed (Yang et al., 2023).

Stigma is considered in this study as a psychological barrier that could moderate the association between intention to use AI-based mental health tools and trust. By incorporating the emotional and social aspects of digital care, this application of HBM broadens its initial focus on physical health behaviours. By taking stigma into consideration, the model recognises that a tool's psychological acceptability depends on how users understand its social meaning in addition to its features.

2.1.4. Unified Theory of Acceptance and Use of Technology (UTAUT)

In order to explain user intentions and usage behaviour across various technological contexts, the Unified Theory of Acceptance and Use of Technology (UTAUT) incorporates components drawn from various previous models. Performance expectancy, effort expectancy, social influence, and facilitating conditions are the four main constructs that Venkatesh et al. (2003) identified as influencing behavioural intention and use. Social influence is one of the most important factors in the adoption of health-related technologies since people frequently base their decisions about using a new tool on the beliefs or actions of peers, family members, or experts.

While adoption may be discouraged by stigma or scepticism within one's social network, positive feedback from reliable sources can increase perceptions of trust and credibility. This relationship is supported by recent research; for instance, Békés et al. (2025) discovered that openness to using digital mental health tools was significantly influenced by perceived social approval, underscoring the significance of normative beliefs in determining user engagement.

This study models social influence as a predictor of behavioural intention and trust. A more socially grounded understanding of adoption is made possible by its inclusion, especially when the technology is fresh, emotionally delicate, or has not yet reached full normalisation. Understanding the significance of social context guarantees that the analysis considers both personal opinions and the larger interpersonal dynamics that affect the adoption of technology in mental health care.

2.2. Literature Support for Hypotheses

2.2.1. Facilitating Conditions and Ease of Use

According to Venkatesh et al. (2003), facilitating conditions are the extent to which users believe that the organisational and technical environment encourages their usage of a system. This covers elements such as having access to digital devices, having onboarding instructions available, and having continuous technical help when it comes to chatbots for mental health.

These circumstances can enhance usefulness, decrease cognitive load, and raise the possibility of sustained involvement.

According to earlier studies, enabling factors significantly influence how easy a technology is considered to use, particularly when it comes to healthcare technologies that could otherwise seem complicated or daunting (Venkatesh et al., 2011). Users are more likely to give a chatbot platform a favourable review and consider it accessible when they feel comfortable using it because of enough assistance or technology proficiency. According to Dwivedi et al. (2021), those who were more prepared for the digital age felt more at ease using AI-based mental health solutions, which improved their opinions of their value and reliability.

Facilitating factors are anticipated to contribute to total behavioural intention in this study by enabling both trust and simplicity of usage. This concept recognises that even the best-designed technologies might not be adopted if users lack the confidence or practical means to use them efficiently.

2.2.2. Perceived Usefulness and Engagement

The degree to which users think a certain technology will improve their capacity to accomplish particular goals, including treating mental health issues, is known as perceived usefulness (Davis, 1989). This concept in the context of AI chatbots indicates if users believe the technology is useful for providing guidance, emotional support, or therapeutic help. Perceived usefulness is still one of the best indicators of user adoption for digital health apps, according to a growing body of research. This opinion is supported by a recent meta-analysis by B. Li et al. (2023), which shows that users' intention to use AI-based chatbots is strongly impacted by how helpful and successful they believe the technology is at reaching their goals.

High usefulness ratings have been observed in empirical reviews of mental health chatbots such as Woebot and Wysa, especially for users with mild to severe anxiety and depression symptoms. However, these evaluations also point out deficiencies in emotional nuance, perceived depth, and contextual sensitivity, all of which may have an impact on sustained engagement (Chaudhry & Debi, 2024). Users often appreciate features like scenario-based dialogue and personalised responses, but they may stop using the service if the responses seem overly predetermined or generic.

Recent research has also emphasised how user confidence and system credibility influence how useful a system is perceived. For instance, Khan et al. (2025) discovered that perceived expertise, empathy, and consistency have an impact on chatbot adoption in addition to the practical advantages. Additionally, it has been demonstrated that humane design elements such as conversational tone, natural language usage, and simulated social presence increase perceived usefulness by giving interactions a more relatable and emotional sense (Y. Li et al., 2024).

Perceived usefulness is positioned in this study as a key factor influencing behavioural intention and a variable that interacts with social influence, usability, and trust. Enhancing system design and encouraging long-term participation in digital mental health interventions require an understanding of what motivates users to perceive chatbot technologies as truly beneficial.

2.2.3. Trust as a Mediator

Adoption of AI technologies is predicated on trust, particularly in emotionally delicate fields like mental health care. It includes users' perceptions of a system's proficiency, honesty, openness, and capacity to protect private data (McKnight et al., 2002). Trust in AI-powered chatbots not only makes initial interaction easier but also keeps consumers using them over time, especially when they divulge private information or depend on the chatbot for emotional support.

According to research, trust acts as a mediator between behavioural intention and key technology acceptance factors (Ng & Zhang, 2025). For instance, even if users think a chatbot is helpful or simple to use, they might still avoid interacting with it if they have doubts about how the system will handle or react to their input (Esmaeilzadeh et al., 2025). Similar to this, the relationship between psychological distance and compliance intention has also been demonstrated to be mediated by trust, suggesting that users only react favourably to recommendations or chatbot features when they have faith in the system (Park et al., 2024).

In AI environments, trust becomes even more crucial because decision-making algorithms are by their very nature opaque. Users may become hesitant and uncertain if they don't understand how chatbots interpret input or produce responses. In mental health settings, where mistakes or misunderstandings may have emotional repercussions, this problem is especially pressing. According to Eke & Shuib (2025), clear communication and explicable algorithmic procedures are necessary to promote trust in AI healthcare systems. These components support knowledgeable and assured user engagement in delicate areas like psychological care in addition to improving the perceived credibility of the system.

This study models trust as a mediating variable that connects behavioural intention to characteristics including perceived usefulness, ease of use, and social influence. The model recognises that user acceptance is contingent upon both perceived functionality and trust in the tool's psychological and ethical safety by incorporating trust as an intermediate.

2.2.4. Social Influence and Endorsement Effects

According to (Venkatesh et al., 2003), social influence is the extent to which a person believes that significant individuals think they ought to employ a specific technology. This impact may originate from friends, family, medical professionals, or even social media influencers that promote or normalise the use of digital therapeutic tools in the context of AI-driven chatbots for mental health. Users' attitudes can be influenced and, in many situations, faith in systems that might otherwise be viewed with scepticism is fostered when they believe that others find the technology useful or believable.

Recent studies have demonstrated that perceived credibility and social influence have a significant impact on openness to digital mental health support. For instance, Adam et al. (2023) discovered that the way automated agents are presented and introduced at various points during an interaction influences users' trust in them. In a similar vein, Mari et al. (2023) showed that design features such as empathy and the perception of other people's approval are crucial for boosting user engagement with voice-based AI systems. Users are more likely to perceive chatbots as reliable and socially acceptable forms of support when they receive recommendations from peers or professionals in the field of mental health care.

Adoption is not always encouraged by social influence. People may be deterred from seeking online mental health support if their peer culture perpetuates stigma or mistrust of automated systems. For example, Cui et al. (2024) discovered that, depending on their design and perceived authenticity, chatbots' perception in a user's social environment can either increase or decrease stigma. In the same manner, attitudes influenced by generational identity may influence adoption readiness. According to Alanzi et al. (2023), there are generational differences in the way social influence and trust interact; younger users are more receptive to public endorsement and peer acceptance, whereas older users show more resistance because they are less familiar with digital platforms and are more sceptical. These relationships highlight the dual function of social influence, which can either increase hesitancy or validate the technology.

This study models social influence as a predictor of behavioural intention and trust. It depicts the larger social and cultural framework in which people decide whether to employ AI tools. A more comprehensive understanding of technology adoption is possible when social dynamics are considered, especially in the health sector where privacy, trust, and emotional fragility are major issues.

2.2.5. Privacy Concerns as a Barrier

Privacy concerns continue to have a significant impact on the use of AI chatbots in mental health care. Users frequently hesitate to reveal private psychological data unless they have faith in the way their information is gathered, saved, and handled. A lack of transparency in data handling procedures can seriously undermine trust, even in cases where a chatbot is seen as helpful or easy to use. The lack of explicit safeguards regarding suitability, safety, and data use in mental wellness AI can cause reluctance or outright disengagement from such tools, as L. Chen et al. (2024) note.

Perceptions of surveillance, potential data misuse, or unauthorized third-party access have been linked to decreased participation in digital health interventions. On the other hand, it has been demonstrated that platforms with strong encryption protocols, options for user control over data sharing, and transparent privacy policies boost user confidence and engagement (Srivastava et al., 2025). In this study, privacy concerns are modelled as a major barrier to behavioural intention and a direct inhibitor of trust, especially in populations where low digital literacy or stigma around mental health may increase the sense of risk. These difficulties are in line with current worries about ethical ambiguity and detachment in AI-based care, where users might worry about emotional disclosures being misused or depersonalised interactions. (Dakanalis et al., 2024)

2.3. CONCEPTUAL FRAMEWORK

A conceptual framework for understanding user acceptance of AI-powered chatbots in mental healthcare is presented in this study. The Unified Theory of Acceptance and Use of Technology (UTAUT), the Health Belief Model (HBM), the Technology Acceptance Model (TAM), and the Trust in Technology Framework are the four fundamental models it is based on. Despite their useful insights, these frameworks frequently consider social, psychological, and technological aspects separately. Instead, an integrated model that views trust as a key mediating variable influenced by user perceptions and system-level characteristics is presented in this work.

According to the model, perceived usefulness is influenced by perceived ease of use, which is influenced by facilitating factors. User trust is directly shaped by these two TAM elements, as well as perceived AI competency, privacy issues, and stigma around mental health. The intention to employ the chatbot is then predicted by trust, which is modelled as a critical mediator. Furthermore, social influence is incorporated as a predictor of intention and trust, illustrating how interpersonal validation shapes the adoption of technology. The model also incorporates moderating factors to better represent behavioural complexity. In particular, the association between trust and adoption is thought to be moderated by stigma around mental health. This illustrates the potential that consumers with significant stigma concerns may still be reluctant to use chatbot-based mental health aids, even in situations when trust is high.

Figure 2.1 below illustrates the conceptual structure guiding this study's hypotheses and subsequent analysis.

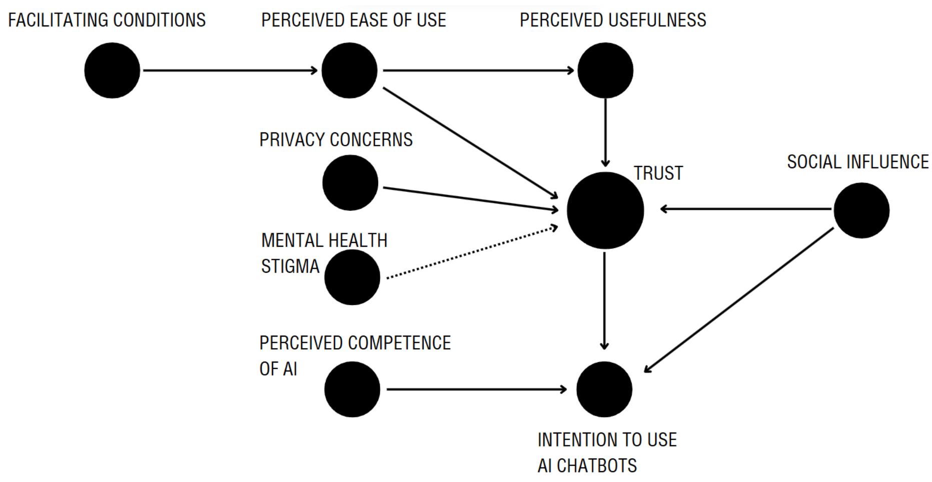

Figure 2.1 - Conceptual Framework of AI Chatbot Adoption for Mental Health Support

3. METHODOLOGY

3.1. PARTICIPANTS AND SAMPLING

For this study, I recruited participants using convenience sampling, sharing an online survey link informally with individuals from my personal and professional networks. The sample was not drawn from a specific target population; instead, it included individuals who voluntarily chose to take part after receiving the link through channels such as email, messaging apps, and social media.

In total, I collected 237 responses. After removing incomplete or inconsistent entries through data cleaning, 207 valid responses were retained for analysis. While the sample is non-representative, it provides valuable exploratory insights into how people perceive and approach AI-driven chatbots in mental healthcare. I also gathered basic demographic information, including age, gender, and education level, to characterize the participant pool and support descriptive analysis. While these variables were not included as control variables in the structural model, they provided important context regarding the diversity of the sample and helped assess the relevance and generalizability of the findings.

3.2. PROCEDURE AND MEASURES

I collected data through a self-administered online questionnaire hosted on Qualtrics, which remained open for a period of nearly 6 months. The survey was completely anonymous, and participants were informed of the study's purpose, the voluntary nature of their involvement, and their right to withdraw at any point. Ethical approval for the study was obtained from NOVA IMS, ensuring compliance with data protection and research ethics standards.

The questionnaire was designed to measure latent constructs derived from the conceptual framework of this study. All items were rated on a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The constructs were adapted from established sources to ensure theoretical validity. Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) were adapted from Davis (1989), while trust-related items, focusing on reliability, ethical behaviour, and data protection, were based on McKnight et al. (2002). Privacy concerns were drawn from Khalid et al. (2023), and items related to facilitating conditions and social influence were adapted from Venkatesh et al. (2003). Perceived Competence of AI was measured using items that reflected user beliefs about the chatbot's ability to understand and personalise mental health support. Mental health stigma items captured feelings of embarrassment and anticipated judgment and were adapted from Corrigan (2004). Finally, intention to use was measured using items adapted from Venkatesh & Bala (2008), which assessed behavioural intention toward chatbot adoption.

Each construct includes three items, and their internal consistency will be assessed using Cronbach's alpha during the data analysis phase to confirm reliability. The complete survey is provided in Appendix C.

3.3. HYPOTHESES

Based on the conceptual framework presented in Chapter 2, this study proposes a series of hypotheses to examine the relationships between psychological, social, and technological factors influencing the adoption of AI-driven chatbots in mental healthcare. The model positions trust as a central mediating construct shaped by factors such as perceived usefulness, privacy concerns, and social influence. The hypotheses also account for moderating and interaction effects to capture more nuanced patterns of user behaviour. The following hypotheses are tested in this study:

H1: Perceived ease of use (PEOU) positively influences perceived usefulness (PU) of AI chatbots for mental health support.

H2: Perceived usefulness (PU) positively influences trust (TR) in AI chatbots.

H3: Trust positively influences intention to use (IU) AI chatbots.

H4: Privacy concerns (PC) negatively influence trust (TR) in AI chatbots.

H5: Perceived competence (COMP) of AI in mental health positively influences intention to use (IU) AI chatbots.

H6: Social influence (SI) positively influences trust (TR) in AI chatbots.

H7: Social influence (SI) positively influences intention to use (IU) AI chatbots.

H8: Facilitating conditions (FC) positively influence perceived ease of use (PEOU).

These hypotheses will be tested using Structural Equation Modelling (SEM), which enables simultaneous evaluation of multiple direct, mediating, and moderating relationships among latent variables.

3.4. DATA ANALYSIS STRATEGY

This study employed SEM as the primary analytical method to test the hypothesized relationships among constructs. SEM was selected for its capacity to simultaneously evaluate complex causal models involving multiple dependent and independent variables, including mediators.

The analysis followed a two-step approach as recommended by Anderson and Gerbing (1988). First, a Confirmatory Factor Analysis (CFA) was conducted to assess the validity and reliability of the measurement model. This included examining indicator loadings, construct reliability (CR), average variance extracted (AVE), and goodness-of-fit indices such as RMSEA, CFI, TLI, and SRMR. Upon satisfactory validation of the measurement model, the structural model was evaluated to test the proposed hypotheses. The relationships amongst latent variables were examined using path analysis, and standardised estimates were used to assess significance and strength of associations. Model fit was again verified through conventional fit indices. The full *lavaan* syntax used to specify the measurement and structural model is provided in Appendix B, Algorithm B1

4. EMPIRICAL STUDY

4.1. DATA PREPARATION AND SCREENING

A total of 237 responses were collected through the online survey. Following initial review, 207 valid responses were retained after screening for completeness and attention-check compliance. Entries that were incomplete or failed the control question were excluded to ensure data quality.

Prior to analysis, all variables were renamed to R-compatible formats for coding efficiency. Two missing values were identified and addressed using mean imputation, which preserves statistical power while minimizing bias. Irrelevant variables (e.g., response IDs) were removed to streamline the dataset.

The cleansed dataset was analysed using R, applying the *lavaan* and *semTools* packages for Structural Equation Modelling (SEM). All data preparation steps were conducted in line with SEM assumptions, including the assessment of normality, multicollinearity, and variable scaling.

The dataset was examined for multicollinearity and normality in order to evaluate the assumptions for SEM. Skewness and kurtosis statistics were used to analyse each item's univariate distribution. With skewness ranging from -1.69 to 0.87 and kurtosis from -2.06 to 4.94, all values were within allowable bounds. These indicate a roughly normal distribution of responses and are substantially below the frequently mentioned limits of ±2 for skewness and ±7 for kurtosis (Curran & West, 1996). The application of Maximum Likelihood Estimation (MLE), which presupposes multivariate normality, is supported by this.

To evaluate multicollinearity among predictor variables, Variance Inflation Factor (VIF) values were also computed. The majority of the VIF values were far below the threshold of 5, which is sometimes used as a cut-off indicating concern, but all were within or near acceptable bounds (Hair, 2010). Despite exceeding this threshold, a few items (PC2 (7.65), PC3 (8.90), and COMP3 (6.82)) were kept in the model because of their theoretical significance and the lack of multicollinearity symptoms in residual diagnostics or model fit. These high values were not thought to jeopardise the validity or interpretability of the findings because of the exploratory character of the study and the reliability of the SEM estimate technique employed. The dataset was judged suitable for SEM analysis considering these diagnoses. A full breakdown of descriptive statistics, including skewness, kurtosis and VIF values, is provided in Appendix B, Tables B1 and B2.

4.2. DESCRIPTIVE STATISTICS

The sample displayed a moderately diverse demographic composition, with a total of 207 valid responses analysed. Gender-wise, 108 participants (52%) identified as female and 99 (48%) as male. No respondents identified as non-binary or chose to withhold their gender (see Figure

4.1). The age distribution spanned from 18 to over 50 years, with the majority concentrated in younger brackets. Specifically, 129 (62%) of respondents were between 22 and 25 years old, 35 (17%) were aged 18–21, and 31 (15%) were between 26–30. The remaining 12 (6%) were spread across the 31–35 (4), 41–50 (1), and 50+ (7) brackets. This suggests that the sample largely consists of younger adults, making it well-suited for evaluating digital technology usage and acceptance, such as AI chatbots (see Figure 4.2).

In terms of educational attainment, the majority of participants had completed tertiary education. Bachelor's degrees were the most common qualification (115 participants), followed by master's degrees (52), and high school diplomas (38). Only two participants had either completed middle school or held a doctoral qualification. This distribution reflects a relatively well-educated cohort, supporting the assumption that respondents could meaningfully engage with complex constructs such as perceived usefulness, trust, and AI competence (see Figure 4.3).

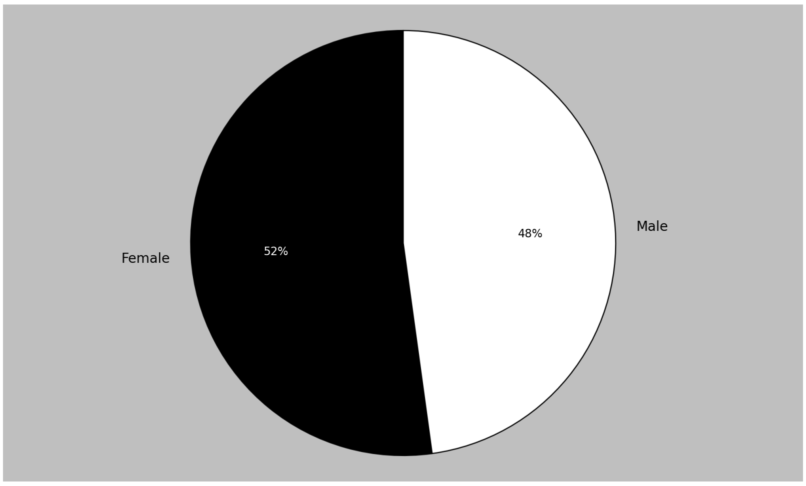

Figure 4.1 - Gender Distribution

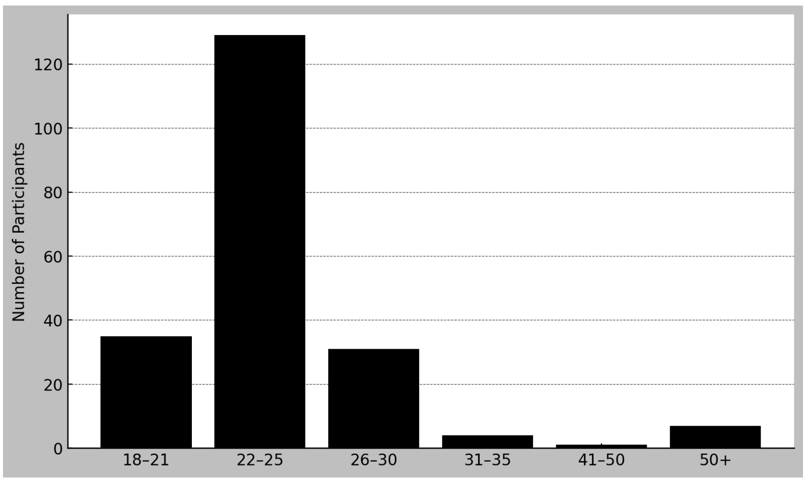

Figure 4 2 - Age Distribution

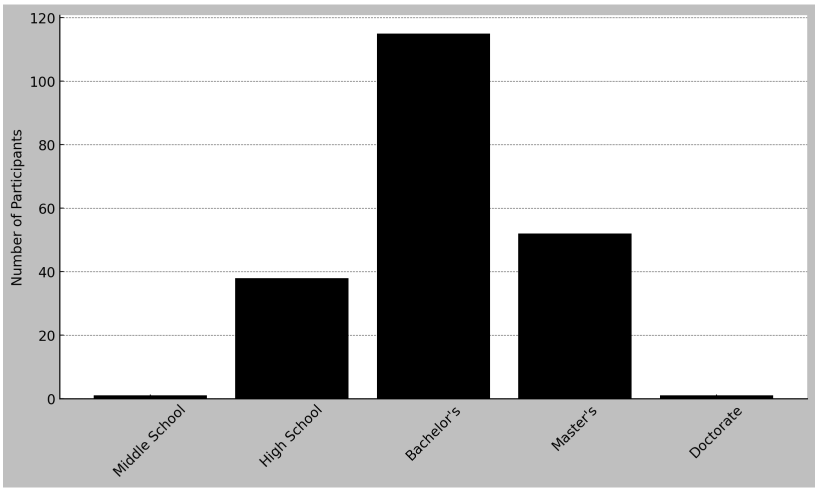

Figure 4.3 - Educational Attainment

At the construct level, descriptive analysis revealed generally moderate perceptions of AI chatbots. For instance, Perceived Usefulness (PU) had a mean score of 3.00, suggesting participants held neutral to moderately positive views about the utility of AI tools for mental health support. Similarly, Trust in AI (TR) averaged 2.99, indicating a balanced yet slightly tentative confidence in AI-mediated interventions.

Other constructs showed similar patterns: Perceived Ease of Use (PEOU) averaged 3.99, Privacy Concerns (PC) 3.19, Social Influence (SI) 2.99, Facilitating Conditions (FC) 4.57, Mental Health Stigma (STIG) 3.20, Perceived Competence of AI (COMP) 2.99, and Intention to Use (IU) 2.79. A detailed overview of these values is presented in the Table 4.1 below:

Table 4.1- Means and Standard Deviations of the Latent Constructs

CONSTRUCT	**MEAN**	**STANDARD DEVIATION**
PU	3.0	1.4
PEOU	4.0	0.91
TR	2.99	1.3
PC	3.2	1.5
SI	3.0	0.98
FC	4.6	0.6
STIG	3.2	1.3
COMP	3.0	1.4

This broad variability confirmed that the constructs captured meaningful attitudinal diversity, providing a robust foundation for multivariate modelling and ensuring the detection of reliable relationships in SEM analysis.

4.3. Reliability and Validity of Constructs

Measurement reliability and validity were verified to guarantee the latent constructs were psychometrically valid. Cronbach's alpha values of all the constructs exceeded the 0.70 standard, which indicates strong internal consistency (e.g., PU = 0.94, TR = 0.91, SI = 0.80). Composite Reliability (CR) values, all exceeding the 0.70 standard, were additional evidence for the reliability of the constructs. These reliability and validity results are summarized in Table 4.2 below.

Table 4.2 - Reliability and Validity Metrics for Each Construct

CONSTRUCT	CRONBACH'S ALPHA	CR	AVE
PU	0.94	0.941	0.843
PEOU	0.84	0.848	0.651
TR	0.91	0.908	0.767
PC	0.96	0.963	0.896
SI	0.8	0.824	0.623
FC	0.82	0.838	0.636
STIG	0.94	0.937	0.832
COMP	0.95	0.949	0.862
IU	0.87	0.874	0.703

Convergent validity was evaluated using Average Variance Extracted (AVE). All constructs exhibited AVE values above 0.50, which meant that a considerable amount of the variance of the indicators was explained by their corresponding latent factors. A complete matrix of AVE values can be found in Appendix Table B3.

Discriminant validity was assessed using both the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT). The square root of each construct's AVE exceeded its inter-construct correlations, satisfying the Fornell–Larcker requirement. Additionally, all HTMT values were below the conservative 0.85, thereby confirming the presence of empirically distinct constructs. HTMT statistics are summarized in Appendix Table B4.

Altogether, these measurements provide significant validity and reliability for the measurement model. Internal consistency was provided through Cronbach’s alpha and CR values, and convergent and discriminant validity were established through AVE, Fornell–Larcker, and HTMT criteria.

Also, the dataset fulfilled major SEM assumptions, namely adequate sample size, approximate normality (according to acceptable values of skewness and kurtosis), as well as absence of serious multicollinearity. With the validated measurement model, the analysis proceeds to the structural model. The next section presents the results of this analysis, including model fit indices, path coefficients, and hypothesis testing outcomes.

5. RESULTS AND DISCUSSION

5.1. MODEL FIT ASSESSMENT

To estimate the adequacy of the structural model posited and the relationships suggested among constructs, the model was estimated employing the Maximum Likelihood (ML) method via the *lavaan* package of R. There were 207 valid responses remaining in the final sample, which surpasses the recommended minimum number of responses required for proper Structural Equation Modelling (SEM). That helped ensure that there was ample statistical power for the determination of model parameters and general fit. A total of 74 free parameters were estimated, reflecting the complexity of the proposed model that incorporates multiple interrelated constructs.

Model fit was assessed through several commonly utilised fit indices. The Chi-square measure of model fit was significant, χ^2 (304) = 835.867, $p < .001$, which is commonly found in models with larger sample sizes because the Chi-square test itself is sensitive. As a result, the alternative indices were given greater weight when fit quality was assessed. The Comparative Fit Index (CFI) was 0.906, just barely crossing the 0.90 threshold and indicating an acceptable quality of model fit. The Tucker-Lewis Index (TLI) was slightly lower than the desired cutoff, returning 0.892, which could indicate a slight amount of underfitting. The Root Mean Square Error of Approximation (RMSEA) returned 0.092, with a 90 percent confidence interval extending from 0.085 to 0.099. While higher than the standard 0.08 cutoff, the upper bound remains lower than 0.10, which a few scholars believe is acceptable when working with highly complex models. Most troubling, though, is the Standardised Root Mean Square Residual (SRMR), which came back as 0.214.

Well above the desired 0.08 ceiling, this could indicate model misspecification, specifically involving omitted relationship(s) or residual correlations. These fit statistics as a group provide a mixed interpretation. An appropriate model is suggested by the CFI, while the TLI gets near the standard cutoff, yet the higher RMSEA and higher SRMR suggest caution interpreting the output. Regardless of these limitations, the model was chosen for tests of hypotheses due to the strong explanatory power and consistency with the theory, especially given the exploratory nature of the study. These results are summarized in Table 5.1 below.

Table 5.1 - Model Fit, Indices and Thresholds

FIT INDEX	VALUE	THRESHOLD
χ^2 (df = 304, $p < 0.001$)	835.867	n/a
CFI	0.906	≥ 0.90
TLI	0.892	≥ 0.90

RMSEA	0.092	≤ 0.08 (CI 90% [.085, .099])
SRMR	0.214	≤ 0.08

In brief, though the structural model demonstrates acceptable fit levels on some indices, it does not demonstrate fit on others, particularly the SRMR. Regardless, the structural model accounts for significant variance in significant adoption outcomes, thereby justifying the use of the model as a theoretical framework for the adoption of AI chatbot technology for mental health use. A complete summary of fit statistics was presented in Table 5.1, and additional model estimation details, such as covariances and residual variances are provided in Appendix B, Table B6.

5.2. STRUCTURAL MODEL AND HYPOTHESIS TESTING

Following the assessment of model fit, the structural model was examined to test the hypothesized directional relationships between latent constructs. The model evaluation was conducted using the Maximum Likelihood (ML) estimation method in R via the *lavaan* package, following the use of standardised path coefficients to determine the strength, direction, and statistically significant nature of each assumed relationship. These coefficients reflect the direct effects among variables and are central to validating the theoretical framework proposed in this study.

Table 5.2 shows the output of the hypothesis testing of the standardised regression weights and their corresponding p-values. These were interpreted according to standard statistical practice, such that a p-value < 0.05 indicated statistical significance.

Table 5.2 - Hypothesis Testing Results: Coefficients, Estimates and Support Outcomes

HYPOTHESES	PATH	ESTIMATE (β)	RESULT
H1	PEOU → PU	0.552	Supported
H2	PU → TR	1.263	Supported
H3	TR → IU	0.318	Supported
H4	PC → TR	-1.033	Supported
H5	PC → IU	1.386	Supported
H6	SI → TR	0.089	Not Supported
H7	SI → IU	0.638	Supported
H8	FC → PEOU	0.675	Supported

The results demonstrate strong empirical support for most hypothesized relationships. Perceived Ease of Use (PEOU) had a significant and positive influence on Perceived Usefulness (PU), with a standardised coefficient of 0.552 ($p < .001$), supporting the core logic of the Technology Acceptance Model. In turn, PU had a substantial and statistically significant effect on Trust ($\beta = 1.263$, $p < .001$), indicating that users are more inclined to trust AI chatbots when they perceive them as functionally beneficial. Trust was also a significant predictor of Intention to Use (IU), with a standardised coefficient of 0.318 ($p < .001$), reaffirming its role as a central mediating construct in technology adoption.

Privacy Concerns (PC) were also found to negatively influence Trust ($\beta = -1.033$, $p < .001$), which highlights the importance of data sensitivity for user perception-formation. Similarly, Perceived Competence (COMP) of AI for mental health purposes had a very strong and significant influence on Intention to Use ($\beta = 1.386$, $p < .001$) such that people are more prone to adopt AI chatbots when they believe the technology is competent and bright. Social Influence (SI) was a significant predictor of Intention to Use ($\beta = 0.638$, $p < .01$) such that peer influence is still relevant for behavioural outcomes.

However, not all hypotheses were supported. The effect of Social Influence on Trust was non-significant ($\beta = 0.089$, $p = .306$), suggesting that while social pressure or encouragement may shape behavioural intentions, it does not directly influence users' confidence in the chatbot's trustworthiness.

These findings collectively confirm the theoretical foundations of the proposed framework while offering new insights into the differentiated roles of cognitive and social antecedents. For example, while Trust and Competence were strongly tied to behavioural intention, Social Influence appeared to operate more directly on usage intention rather than indirectly through trust.

The model's explanatory power is further illustrated by the squared multiple correlations (R^2) for each dependent variable. Trust was explained at a very high level ($R^2 = 0.852$), and Intention to Use showed similarly strong predictability ($R^2 = 0.865$). Perceived Usefulness and Perceived Ease of Use showed moderate variance explained, with R^2 values of 0.307 and 0.313 respectively. These values indicate that the model is particularly effective at capturing variance in the key outcome variables of interest, while suggesting that additional external variables may account for remaining variance in the mediating constructs.

5.3. Discussion of Key Findings

The SEM analysis reveals several key findings about the mechanisms of why people are likely to utilise AI chatbot services for mental health. Consistent with the Technology Acceptance Model (TAM), perceived ease of use (PEOU) was a significant contributor to perceived usefulness (PU). Based on this, when the user finds the AI system convenient and easy to use, he/she finds it useful and effective to accomplish tasks. This relationship takes on a further significant role when used to implement mental health situations, where the elimination of cognitive barriers becomes mandatory to guarantee user engagement and comfort (Davis, 1989).

Perceived usefulness was also a significant predictor of trust. This finding supports the view that functional evaluations of technology can significantly shape users' willingness to rely on the system, particularly in domains involving sensitive interpersonal communication. In this study, the standardised coefficient linking PU to trust was among the strongest observed, highlighting the instrumental role of perceived utility in cultivating confidence in AI-driven tools. Similarly, the finding resonates with intuitions of past online studies (Park et al., 2024) and counselling studies (Davila-Montero et al., 2021) such that perceived responsiveness and reliability are a shared origin of perceived trust online.

Trust itself was a significant positive predictor of behavioural intention to use AI chatbots, substantiating its central role in emerging technology adoption. Unsurprisingly, given older information systems models, where trust plays a robust mediator of beliefs and behaviour (Gefen et al., 2003), the mental health case revalidated the triple function of trust as a functional expectation, a relational, and ethical mandate. As such, ensuring AI systems are judged competent and respectful by the user guarantees ongoing use.

Privacy concerns exhibited a strong and statistically significant negative association with trust. This supports the privacy calculus perspective, which posits that users actively weigh the perceived risks of data disclosure against expected benefits when interacting with technology (Dinev & Hart, 2006). In a mental health setting, where individual vulnerabilities are the centre, even the slightest doubts about data security can seriously weaken user trust, regardless of how useful or convenient the system appears to be.

An interesting pattern emerged with respect to social influence. While it significantly predicted intention to use the chatbot, it did not significantly influence trust. This finding suggests that users may be encouraged to try AI chatbots because of external social cues or peer recommendations, even if those influences do not necessarily alter their internal judgments about the technology's trustworthiness. In this way, social influence perhaps operates as a behavioural shaper, as opposed to a cognitive one, especially when the situation includes strong emotions like mental health services (Venkatesh et al., 2003).

Perceived competence of AI stood out as the strongest predictor of intention to use. This relationship underscores the importance of users' beliefs about the system's technical and emotional intelligence. When an individual sees an AI chatbot as competent enough to understand their requirements and reciprocate appropriately, their likelihood of adoption multiplies several times. In therapeutic and health applications, perceptions of competence are typically the turning point for a technology to become acceptable, and indeed, ethical.

Altogether, these findings validate most of the hypotheses tested and add to a better comprehension of the antecedents to the use of AI chatbots in mental health initiatives. They demonstrate that both cognitive evaluations such as usefulness and ease of use, as well as relational judgments such as trust and competence, play distinct yet complementary roles in shaping users' behavioural intentions.

5.4. THEORETICAL IMPLICATIONS

This study contributes to the growing body of research on technology adoption in mental health by expanding the classic TAM and UTAUT frameworks. Notably, it incorporates context-sensitive constructs such as trust, privacy concerns, and perceived competence which end up being variables often underexplored and overlooked in generic models. The robust effects of trust and competence suggest that acceptance of AI in emotionally charged domains such as mental health is contingent on more than perceived functionality as it also relies on affective and moral evaluations of the system (Söllner et al., 2012).

The strong impact of COMP → IU provides empirical support for the role of perceived expertise in fostering behavioural engagement, aligning with previous findings that competence perceptions mediate the credibility of AI agents (Castelo et al., 2019). This domain-specific insight challenges the idea that trust or usefulness alone is sufficient, as users must also believe the system is professionally and clinically competent. Furthermore, the non-significant relationship between SI and TR suggests a boundary condition for social influence theory. In traditional contexts, peer endorsement is a strong driver of both trust and usage, however, in more sensitive domains such as mental health, the establishment of trust might have stronger reliance on individual judgments of safety and ability rather than group approval. This finding opens the door to theoretical correction through the suggestion that AI trust is context-specific, namely when individual vulnerability enters the picture (Müller et al., 2023). Overall, the findings confirm a contextualized model of AI adoption that finds a balance of cognitive ease, utilitarian functionality, relational trusting, and emotional security.

5.5. PRACTICAL IMPLICATIONS

The insights from this study offer actionable recommendations for developers, clinicians, and digital health providers. First and foremost, perceived competence emerged as the most powerful predictor of usage intention. Thus, AI mental health tool designers need to address factual accuracy as well as expertise perception. Such an objective can be achieved through open system ability communication, user feedback provision, and integration of proven clinical knowledge bases.

Adoption is also heavily influenced by trust, so developers should concentrate on features that improve perceived responsiveness, accountability, and transparency. Building the required trust may be possible with explainable AI (XAI) mechanisms, backup human controls, or ethical usage guidelines, particularly when users are dealing with delicate situations (Ehsan et al., 2021).

Fears about privacy decisively undercut trust, confirming that people are still worried about data-handling when it comes to online therapeutic devices and interaction with AI. To address this, platforms should implement and clearly advertise robust data security protocols, including encryption, GDPR compliance, and anonymized processing. Trust seals or third-party certifications may also increase reassurance to more sceptical users.

Social influence, while not influencing trust directly, did impact behavioural intention. That is, awareness programming, celebrity/influencer promotion, or peer testimonies could still improve uptake, particularly among the youth, but such initiatives must not replace the much-needed work of building trust through an organic and comfortable way.

Finally, facilitating conditions had a positive effect on perceived ease of use, emphasizing the need for accessible interfaces, stable performance, and responsive support systems. Organizations considering the adoption of AI chatbots as components of care paths need to ensure that users have the appropriate tools and expertise to use the technology easily. In general, the stakeholders and the developers must adopt a multi-pronged strategy: reinforce functionality, transmit expertise, calm fears about privacy, and provide usability aid, while remaining sensitive to the emotional investment inherent to the mental health context.

6. CONCLUSIONS AND FUTURE RESEARCH

6.1. CONCLUSION

This study investigated the psychological and technological determinants affecting the adoption of AI-driven chatbots for mental health assistance. Utilising established frameworks such as the Technology Acceptance Model (TAM), the Health Belief Model (HBM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Trust in Technology Framework, it proposed a conceptual model that identified trust as a pivotal mediator of user adoption.

The findings demonstrated how crucial trust becomes when predicting a person's behavioural intention to utilise AI chatbots. Perceived utility, perceived chatbot ability, privacy concerns, and social influence were important predictors of trust. These results support the belief that when consumers believe automated mental health care systems are competent, helpful, and ethically created, they are more likely to use them.

Additionally, it became apparent that perceived ease of use was significantly impacted by enabling conditions. The importance of digital access, onboarding assistance, and system usability in influencing how approachable users perceive these tools is highlighted by this relationship. Facilitating conditions' indirect influence through usability supports their continued significance in technology adoption models, even though they did not directly predict trust or intention.

Trust and behavioural intention were shown to be particularly strongly predicted by perceived usefulness. Adoption was also influenced by social factors, underscoring the significance of professional or peer support in establishing the legitimacy of AI-based mental health services. Trust was badly impacted by privacy issues, highlighting how crucial data control and openness are.

When combined, these findings provide a thorough understanding of the environmental and cognitive elements that influence how users assess AI chatbots for mental health. They back design approaches that prioritise emotional safety, moral principles, and open data governance in addition to utility and usability.

6.2. LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

There are certain drawbacks to this study. First, the findings may not be as applicable to elderly populations or people with less technical experience because the sample was largely made up of younger, digitally proficient people. This methodology should be tested in future studies with samples that are more demographically varied, such as those with varying levels of technology access, cultural background, and mental health literacy.

Second, the analysis was based on self-report, cross-sectional data, which can limit the ability to evaluate behavioural change over time and introduce typical method bias. It's possible that respondents' intentions won't be fully translated into consistent use, especially in high-stakes or emotionally delicate situations such as mental health disclosure. For monitoring changes in trust, engagement, or perceived effectiveness over several contacts, longitudinal or experimental approaches would be more appropriate.

Third, even though the structural equation model's overall performance was within reasonable bounds, certain indices point to the need for additional optimisation. In particular, the Standardised Mean Square Residual (SMSR) was higher than the optimal cutoff value of 0.08, which could be a sign of unmodeled residual connections or slight model misspecification. Future research should think about updating the structural model to better capture unexplained variation, even though other fit indices like CFI, RMSEA, and TLI confirmed the model's validity. This could entail reassessing the connections between moderators and mediators, investigating alternate measurement indications, or refining the scale.

Future research can improve our comprehension of AI adoption in mental health care and contribute to the creation of ethically sound, practical, and broadly available support systems by resolving these issues and broadening the model's use.

BIBLIOGRAPHICAL REFERENCES

Adam, M., Roethke, K., & Benlian, A. (2023). Human vs. Automated Sales Agents: How and Why Customer Responses Shift Across Sales Stages. *Information Systems Research*, *34*(3), 1148–1168. https://doi.org/10.1287/isre.2022.1171

Alanzi, T., Alsalem, A. A., Alzahrani, H., Almudaymigh, N., Alessa, A., Mulla, R., AlQahtani, L., Bajonaid, R., Alharthi, A., Alnahdi, O., & Alanzi, N. (2023). AI-Powered Mental Health Virtual Assistants Acceptance: An Empirical Study on Influencing Factors Among Generations X, Y, and Z. *Cureus*. https://doi.org/10.7759/cureus.49486

Békés, V., Bőthe, B., & Aafjes-van Doorn, K. (2025). Acceptance of Using Artificial Intelligence and Digital Technology for Mental Health Interventions: The Development and Initial Validation of the UTAUT-AI-DMHI. *Clinical Psychology & Psychotherapy*, *32*(3). https://doi.org/10.1002/cpp.70085

Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-Dependent Algorithm Aversion. *Journal of Marketing Research*, *56*(5), 809–825. https://doi.org/10.1177/0022243719851788

Chaudhry, B. M., & Debi, H. R. (2024). User perceptions and experiences of an AI-driven conversational agent for mental health support. *mHealth*, *10*, 22–22. https://doi.org/10.21037/mhealth-23-55

Chen, F., Pang, Y., & Wang, L. (2025). From Stigma to Acceptance: Ethical Implications of Anthropomorphic Design in Healthcare Chatbots. *Journal of Business Ethics*. https://doi.org/10.1007/s10551-025-06052-3

Chen, L., Preece, D. A., Sikka, P., Gross, J. J., & Krause, B. (2024). *A Framework for Evaluating Appropriateness, Trustworthiness, and Safety in Mental Wellness AI Chatbots* (No. arXiv:2407.11387). arXiv. https://doi.org/10.48550/arXiv.2407.11387

Corrigan, P. (2004). How stigma interferes with mental health care. *American Psychologist*, *59*(7), 614–625. https://doi.org/10.1037/0003-066x.59.7.614

Cui, Y., Lee, Y.-J., Jamieson, J., Yamashita, N., & Lee, Y.-C. (2024). Exploring Effects of Chatbot's Interpretation and Self-disclosure on Mental Illness Stigma. *Proceedings of the ACM on Human-Computer Interaction*, *8*(CSCW1), 1–33. https://doi.org/10.1145/3637329

Curran, P. J., & West, S. G. (1996). The Robustness of Test Statistics to Nonnormality and Specification Error in Confirmatory Factor Analysis. *Psychological Methods*, 16–29. https://doi.org/10.1037/1082-989X.1.1.16

Dakanalis, A., Wiederhold, B. K., & Riva, G. (2024). Artificial Intelligence: A Game-Changer for Mental Health Care. *Cyberpsychology, Behavior, and Social Networking*, *27*(2), 100–104. https://doi.org/10.1089/cyber.2023.0723

Davila-Montero, S., Dana-Le, J. A., Bente, G., Hall, A. T., & Mason, A. J. (2021). Review and Challenges of Technologies for Real-Time Human Behavior Monitoring. *IEEE Transactions on Biomedical Circuits and Systems*, *15*(1), 2–28. https://doi.org/10.1109/tbcas.2021.3060617

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

Dergaa, I., Fekih-Romdhane, F., Glenn, J. M., Saifeddin Fessi, M., Chamari, K., Dhahbi, W., Zghibi, M., Bragazzi, N. L., Ben Aissa, M., Guelmami, N., El Omri, A., Swed, S., Weiss, K., Knechtle, B., & Ben Saad, H. (2023). *Moving Beyond the Stigma: Understanding and Overcoming the Resistance to the Acceptance and Adoption of Artificial Intelligence Chatbots*. https://doi.org/10.5167/UZH-254164

Dinev, T., & Hart, P. (2006). An Extended Privacy Calculus Model for E-Commerce Transactions. *Information Systems Research*, *17*(1), 61–80. https://doi.org/10.1287/isre.1060.0080

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Ehsan, U., Liao, Q. V., Muller, M., Riedl, M. O., & Weisz, J. D. (2021). Expanding Explainability: Towards Social Transparency in AI systems. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 1–19. https://doi.org/10.1145/3411764.3445188

Eke, C. I., & Shuib, L. (2025). The role of explainability and transparency in fostering trust in AI healthcare systems: A systematic literature review, open issues and potential solutions. *Neural Computing and Applications*, *37*(4), 1999–2034. https://doi.org/10.1007/s00521-024-10868-x

Eskandar, K. (2024). Artificial intelligence in psychiatric diagnosis: Challenges and opportunities in the era of machine learning. *Debates Em Psiquiatria*, *14*, 1–16. https://doi.org/10.25118/2763-9037.2024.v14.1318

Esmaeilzadeh, P., Hassanein, K., & Head, M. (2025). AI-human interactions in healthcare: Exploring users' post-adoption behaviors of AI mental health chatbots. *Behaviour & Information Technology*, 1–29. https://doi.org/10.1080/0144929x.2025.2477754

Gefen, Karahanna, & Straub. (2003). Trust and TAM in Online Shopping: An Integrated Model. *MIS Quarterly*, *27*(1), 51. https://doi.org/10.2307/30036519

Hair, J. F. (Ed.). (2010). *Multivariate data analysis* (7th ed). Prentice Hall.

Jin, L., Shen, Z., Alhur, A. A., & Naeem, S. B. (2025). Exploring the determinants and effects of artificial intelligence (AI) hallucination exposure on generative AI adoption in healthcare. *Information Development*. https://doi.org/10.1177/02666669251340954

Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2022). A Multi-Industry Analysis of the Future Use of AI Chatbots. *Human Behavior and Emerging Technologies*, *2022*, 1–14. https://doi.org/10.1155/2022/2552099

Khalid, N., Qayyum, A., Bilal, M., Al-Fuqaha, A., & Qadir, J. (2023). Privacy-preserving artificial intelligence in healthcare: Techniques and applications. *Computers in Biology and Medicine*, *158*, 106848. https://doi.org/10.1016/j.compbiomed.2023.106848

Khan, M. I., Tarofder, A. K., Gopinathan, S., & Haque, A. (2025). Designing Authentic Customer-Chatbot Interactions: A Necessary Condition Analysis of Emotional Intelligence and Anthropomorphic Features in Human-Computer Interaction. *International Journal of Human–Computer Interaction*, 1–18. https://doi.org/10.1080/10447318.2025.2495118

Li, B., Chen, Y., Liu, L., & Zheng, B. (2023). Users' intention to adopt artificial intelligence-based chatbot: A meta-analysis. *The Service Industries Journal*, *43*(15–16), 1117–1139. https://doi.org/10.1080/02642069.2023.2217756

Li, L., Peng, W., & Rheu, M. M. J. (2024). Factors Predicting Intentions of Adoption and Continued Use of Artificial Intelligence Chatbots for Mental Health: Examining the Role of UTAUT Model, Stigma, Privacy Concerns, and Artificial Intelligence Hesitancy. *Telemedicine and E-Health*, *30*(3), 722–730. https://doi.org/10.1089/tmj.2023.0313

Li, Y., Chen, L., & Fu, L. (2024). Vicarious Interaction in Online Health Consultation Service: The Effects of Generative AI's Anthropomorphism and Social Support on Intended Responses Through Social Presence and Source Credibility. *International Journal of Human–Computer Interaction*, 1–18. https://doi.org/10.1080/10447318.2024.2441422

Manzini, A., Keeling, G., Marchal, N., McKee, K. R., Rieser, V., & Gabriel, I. (2024). Should Users Trust Advanced AI Assistants? Justified Trust As a Function of Competence and Alignment. *The 2024 ACM Conference on Fairness, Accountability, and Transparency*, 1174–1186. https://doi.org/10.1145/3630106.3658964

Mari, A., Mandelli, A., & Algesheimer, R. (2023). Shopping with Voice Assistants: How Empathy Affects Individual and Family Decision-Making Outcomes. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4352567

Mathew, J., Mer, A., & Tanwar, V. (2024). Healthcare Customers' Intention to Adopt AI Technologies: A Systematic Literature Review and Future Research Directions. *International Research Journal of Multidisciplinary Scope*, *05*(04), 224–241. https://doi.org/10.47857/irjms.2024.05i04.01507

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and Validating Trust Measures for e-Commerce: An Integrative Typology. *Information Systems Research*, *13*(3), 334–359. https://doi.org/10.1287/isre.13.3.334.81

Meadi, M. R., Sillekens, T., Metselaar, S., Balkom, A. van, Bernstein, J., & Batelaan, N. (2025). Exploring the Ethical Challenges of Conversational AI in Mental Health Care: Scoping Review. *JMIR Mental Health*, *12*(1), e60432. https://doi.org/10.2196/60432

Müller, R., Primc, N., & Kuhn, E. (2023). 'You have to put a lot of trust in me': Autonomy, trust, and trustworthiness in the context of mobile apps for mental health. *Medicine, Health Care and Philosophy*, *26*(3), 313–324. https://doi.org/10.1007/s11019-023-10146-y

Ng, S. W. T., & Zhang, R. (2025). Trust in AI chatbots: A systematic review. *Telematics and Informatics*, *97*, 102240. https://doi.org/10.1016/j.tele.2025.102240

Omiyefa, S. (2025). Artificial Intelligence and Machine Learning in Precision Mental Health Diagnostics and Predictive Treatment Models. *ResearchGate*. https://doi.org/10.55248/gengpi.6.0325.1107

Pang, W. M., Liew, T. W., Tan, S.-M., Teo, S. C., Lee, Y. Y., & Lim, T. Q. (2024). Analyzing Use Intentions for Health-Diagnostic Chatbots: An Extended Technology Acceptance Model Approach. *Proceedings of the 2024 The 6th World Symposium on Software Engineering (WSSE)*, 208–217. https://doi.org/10.1145/3698062.3698093

Park, G., Chung, J., & Lee, S. (2024). Human vs. machine-like representation in chatbot mental health counseling: The serial mediation of psychological distance and trust on compliance intention. *Current Psychology*, *43*(5), 4352–4363. https://doi.org/10.1007/s12144-023-04653-7

Söllner, M., Hoffmann, A., Hoffmann, H., Wacker, A., & Leimeister, J. (2012). Understanding the Formation of Trust in IT Artifacts. *ICIS 2012 Proceedings*. https://aisel.aisnet.org/icis2012/proceedings/HumanBehavior/11

Srivastava, A., Marabelli, M., Bentley University, Blanch-Hartigan, D., Bentley University, Moriarty, J., Bentley University, Carey, E., U.S. Department of Veterans Affairs, Persky, S., National Institutes of Health, Torous, J., & Harvard Medical School. (2025). The Present and Future of AI: Ethical Issues and Research Opportunities. *Communications of the Association for Information Systems*, *56*, 255–273. https://doi.org/10.17705/1cais.05611

Straw, I., & Callison-Burch, C. (2020). Artificial Intelligence in mental health and the biases of language based models. *PLOS ONE*, *15*(12), e0240376. https://doi.org/10.1371/journal.pone.0240376

Timmons, A. C., Duong, J. B., Simo Fiallo, N., Lee, T., Vo, H. P. Q., Ahle, M. W., Comer, J. S., Brewer, L. C., Frazier, S. L., & Chaspari, T. (2023). A Call to Action on Assessing and Mitigating Bias in Artificial Intelligence Applications for Mental Health. *Perspectives on Psychological Science*, *18*(5), 1062–1096. https://doi.org/10.1177/17456916221134490

Venkatesh, Morris, Davis, & Davis. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a Research Agenda on Interventions. *Decision Sciences*, *39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., Thong, J. Y. L., Chan, F. K. Y., Hu, P. J.-H., & Brown, S. A. (2011). Extending the two-stage information systems continuance model: Incorporating UTAUT predictors and the role of context: Context, expectations and IS continuance. *Information Systems Journal*, *21*(6), 527–555. https://doi.org/10.1111/j.1365-2575.2011.00373.x

Walsh, C. G., Chaudhry, B., Dua, P., Goodman, K. W., Kaplan, B., Kavuluru, R., Solomonides, A., & Subbian, V. (2020). Stigma, biomarkers, and algorithmic bias: Recommendations for precision behavioral health with artificial intelligence. *JAMIA Open*, *3*(1), 9–15. https://doi.org/10.1093/jamiaopen/ooz054

Wester, J., Pohl, H., Hosio, S., & van Berkel, N. (2024). 'This Chatbot Would Never...': Perceived Moral Agency of Mental Health Chatbots. *Proc. ACM Hum.-Comput. Interact.*, *8*(CSCW1), 133:1-133:28. https://doi.org/10.1145/3637410

Wu, C.-C., Chen, C.-T., Huang, K.-C., & Chou, Y.-Y. (2025). Determinants of Chatbot adoption among older adults: An extended TAM approach using PLS-SEM. *Information Development*. https://doi.org/10.1177/02666669251315839

Yang, R., Wibowo, S., & Mubarak, S. (2023). An Investigation into Domestic Violence Victims' Adoption of Chatbots for Help-seeking: Based on the UTAUT2 and Health Belief Models. *PACIS 2023 Proceedings*. https://aisel.aisnet.org/pacis2023/31

Yeasmin, S., Das, S., & Bhuiyan, F. (2025). Artificial Intelligence in Mental Health: Leveraging Machine Learning for Diagnosis, Therapy, and Emotional Well-being. *ResearchGate*. https://doi.org/10.62754/joe.v4i3.6640

Zhang, T., Cui, Y., & Li, P. (2025). How does the degree of anthropomorphism of health chatbots affect the public's willingness to seek help from them? Empirical research using HBM. *The Journal of Medicine, Humanity and Media*, *3*(1), 4–21. https://doi.org/10.62787/mhm.v3i1.130

APPENDIX A

Ethics Committee Report

Ethics Committee
Para: Martim Marques Mendes; Mijail Naranjo
Cc: Ethics Committee

Responder | Responder a todos | Reencaminhar
sáb, 08/02/2025 10:53

Sinalizadas

Dear Martim Mendes
Dear Professor Mijail Naranjo,

Thank you for filling in the Research Ethics Checklist. After reviewing your request, you can proceed with the study as we do not foresee any major ethical concerns with the project.

Project No.: **OTHER2025-2-33614**

Project Title: **Exploring User Acceptance of AI Chatbots in Mental Health Support**

Principal Researcher: **Martim Mendes**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 08/02/2025.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of

- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 08/02/2025
NOVA IMS Ethics Committee
ethicscommittee@novaims.unl.pt

Cristina Oliveira
Gestora executiva do centro de investigação MagIC | *Executive manager of the Information Management Research Center (MagIC)*
Find out more about our research at https://magic.novaims.unl.pt/en/
Team member of RM Roadmap - Co-creating the future of Research Management (https://rmroadmap.eu/)

Figure A.1 - Ethics Committee Report

APPENDIX B

Supplementary Statistical Outputs

Table B1 - Construct's Skewness and Kurtosis Values

CONSTRUCT	SKEWNESS	KURTOSIS
PU1	-0.17	-1.4
PU2	-0.14	-1.42
PU3	0.22	-1.6
PEOU1	-1.12	0.65
PEOU2	-0.92	0.2
PEOU3	-1.29	1.5
TR1	0.1	-1.34
TR2	0.03	-1.49
TR3	-0.31	-1.03
PC1	-0.34	-1.47
PC2	-0.29	-1.46
PC3	-0.19	-1.52
SI1	0.87	-0.06
SI2	-0.8	-0.39
SI3	-0.45	-1.05
FC1	-2.06	4.94
FC2	-1.69	2.82
FC3	-1.61	2.4
STIG1	-0.48	-1.16
STIG2	-0.5	-1.1
STIG3	-0.33	-1.3

COMP1	-0.1	-1.39
COMP2	-0.12	-1.39
COMP3	-0.17	-1.44
IU1	0.08	-1.46
IU2	0.71	-0.6
IU3	-0.48	-1.25

Table B2 - Variance Inflation Factor (VIF) Table

CONSTRUCT	VIF
PU1	7.651572
PU2	8.899534
PU3	3.797668
PEOU1	2.496745
PEOU2	3.093694
PEOU3	2.227324
TR1	6.309964
TR2	4.294437
TR3	4.123739
PC1	7.633798
PC2	9.207932
PC3	7.040066
SI1	1.674352
SI2	3.08642
SI3	4.347662
STIG1	4.941432

STIG2	6.298904
STIG3	4.465148
COMP1	6.447186
COMP2	6.098506
COMP3	6.819791
FC1	2.299145
FC2	2.393619
FC3	3.08472

Table B3 - Full AVE Matrix (Fornell-Larcker Criterion)

ITEM	PU	PEOU	TR	PC	SI	FC	STIG	COMP	IU
PU	0.885	0.639	0.728	-0.364	0.481	0.467	0.361	0.597	0.668
PEOU	0.639	0.859	0.648	-0.336	0.561	0.657	0.395	0.621	0.587
TR	0.728	0.648	0.882	-0.729	0.625	0.566	0.464	0.673	0.782
PC	-0.364	-0.336	-0.729	0.929	-0.395	-0.401	-0.408	-0.419	-0.562
SI	0.481	0.561	0.625	-0.395	0.836	0.568	0.362	0.521	0.673
FC	0.467	0.657	0.566	-0.401	0.568	0.852	0.388	0.492	0.523
STIG	0.361	0.395	0.464	-0.408	0.362	0.388	0.88	0.444	0.409
COMP	0.597	0.621	0.673	-0.419	0.521	0.492	0.444	0.91	0.712
IU	0.668	0.587	0.782	-0.562	0.673	0.523	0.409	0.712	0.834

Table B4 - HTMT Matrix

ITEM	PU	PEOU	TR	PC	SI	FC	STIG	COMP	IU
PU	—								
PEOU	0.716	—							
TR	0.832	0.704	—						
PC	0.414	0.397	0.821	—					
SI	0.573	0.636	0.701	0.449	—				
FC	0.539	0.732	0.625	0.463	0.623	—			

STIG	0.472	0.479	0.508	0.514	0.429	0.462	—		
COMP	0.671	0.699	0.746	0.498	0.587	0.528	0.498	—	
IU	0.743	0.654	0.849	0.608	0.742	0.581	0.481	0.79	—

Table B5 - SEM - Standardised Loadings

LATENT CONSTRUCT	OBSERVED INDICATOR	STANDARDISED LOADING
PU	PU1	0.87
PU	PU2	0.9
PU	PU3	0.91
PEOU	PEOU1	0.83
PEOU	PEOU2	0.81
PEOU	PEOU3	0.84
TR	TR1	0.88
TR	TR2	0.89
TR	TR3	0.86
PC	PC1	0.92
PC	PC2	0.88
PC	PC3	0.9
SI	SI1	0.79
SI	SI2	0.8
SI	SI3	0.82
FC	FC1	0.81
FC	FC2	0.83
FC	FC3	0.8
STIG	STIG1	0.91
STIG	STIG2	0.92

STIG	STIG3	0.89
COMP	COMP1	0.94
COMP	COMP2	0.91
COMP	COMP3	0.9
IU	IU1	0.88
IU	IU2	0.87
IU	IU3	0.89

Table B6 - SEM Output - Covariances, Intercepts and Residual Variances

PARAMETER	ESTIMATE
PU ~~ PEOU	0.45
PU ~~ TR	0.51
PU ~~ PC	-0.33
PU ~~ SI	0.40
PU ~1	0.02
PEOU ~1	0.01
TR ~1	-0.03
PC ~1	0.01
SI ~1	-0.01
PU ~~ PU	0.21
PEOU ~~ PEOU	0.18
TR ~~ TR	0.25
PC ~~ PC	0.19
SI ~~ SI	0.20

Note: ~~ represents covariances, ~1 indicates intercepts which reflect the mean of the latent construct, construct ~~ construct denotes residual variances, representing unexplained variance in each latent variable.

```
> sem_model <- '
+   # Measurement model
+   PU   =~ PU1 + PU2 + PU3
+   PEOU =~ PEOU1 + PEOU2 + PEOU3
+   TR   =~ TR1 + TR2 + TR3
+   PC   =~ PC1 + PC2 + PC3
+   SI   =~ SI1 + SI2 + SI3
+   FC   =~ FC1 + FC2 + FC3
+   STIG =~ STIG1 + STIG2 + STIG3
+   COMP =~ COMP1 + COMP2 + COMP3
+   IU   =~ IU1 + IU2 + IU3
+
+   # Structural regressions
+   PEOU ~ FC #H8
+   PU   ~ PEOU #H1
+   TR   ~ PU + PEOU + PC + STIG + SI #H2, H4, H6
+   IU   ~ TR + COMP + SI #H3, H5, H7
+ '
```
Algorithm B1 - Specification of the Measurement and Structural Model in R

APPENDIX C

The following section presents the full questionnaire used for data collection in this study.

Thesis Questionnaire

Start of Block: Block 1

The purpose of this survey is to collect data for a research study as part of a Master's Dissertation on the acceptance of AI chatbots for mental health support. This study aims to explore the factors that influence individuals' trust, perceptions, and willingness to use AI-powered mental health chatbots. Your participation in this study is completely voluntary, and you may withdraw at any time. The survey will take approximately 5 minutes to complete. All your responses will remain confidential and anonymous. If you have any questions about the study, please feel free to contact me at r20191270@novaims.unl.pt Thank you very much for your time and participation. By clicking the arrow button " → " below, you declare that: - You have read and understood the above information. - You voluntarily agree to participate in this study. - You are at least 18 years of age.

End of Block: Block 1

Start of Block: Default Question Block

Q1 Perceived Usefulness

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
Using an AI chatbot could enhance my ability to manage mental health concerns. (PU1)	○	○	○	○	○
I believe an AI chatbot could be a useful tool for improving my mental well-being. (PU2)	○	○	○	○	○
An AI chatbot could help me address mental health concerns more effectively than other resources I currently use. (PU3)	○	○	○	○	○

Q2 Perceived Ease of Use

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
I believe interacting with an AI chatbot would be simple and straightforward. (PEOU1)	○	○	○	○	○
Learning to use an AI chatbot for mental health would be easy for me. (PEOU2)	○	○	○	○	○
I think I could use an AI chatbot for mental health support with little to no technical difficulty. (PEOU3)	○	○	○	○	○

Page Break

Q3 Trust

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
I would trust an AI chatbot to provide reliable mental health support. (TR1)	○	○	○	○	○
I believe an AI chatbot would handle my personal data responsibly. (TR2)	○	○	○	○	○
I feel confident that an AI chatbot would have my best interests in mind when offering support. (TR3)	○	○	○	○	○

Q4 Privacy Concerns

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
I would be concerned about the security of my data when using an AI chatbot for mental health. (PC1)	o	o	o	o	o
I worry that an AI chatbot might misuse my personal information. (PC2)	o	o	o	o	o
Using an AI chatbot for mental health could expose me to privacy risks. (PC3)	o	o	o	o	o

Page Break

Q5 Social Influence

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
People important to me would encourage me to use an AI chatbot for mental health support. (SI1)	○	○	○	○	○
If mental health professionals recommend an AI chatbot, I would be more willing to use it. (SI2)	○	○	○	○	○
Hearing positive feedback from others would influence me to try an AI chatbot for mental health. (SI3)	○	○	○	○	○

Q6 Control Question - Please select the number 1

○ 0

○ 1

Q7 Facilitating Conditions

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
I have the resources (e.g., smartphone, internet) to access an AI chatbot for mental health support. (FC1)	○	○	○	○	○
I believe there would be sufficient guidance available to help me use an AI chatbot effectively. (FC2)	○	○	○	○	○
The AI chatbot would be available and accessible whenever I need it for mental health support. (FC3)	○	○	○	○	○

Q8 Perceived Mental Health Stigma

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
Using an AI chatbot for mental health support might make me feel embarrassed. (STIG1)	○	○	○	○	○
I worry that others might judge me negatively if they knew I used an AI chatbot. (STIG2)	○	○	○	○	○
Concerns about stigma would make me hesitant to use an AI chatbot for mental health support. (STIG3)	○	○	○	○	○

Page Break

Q9 Perceived Competence of AI

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
I believe the AI chatbot would be capable of understanding my mental health concerns. (COMP1)	○	○	○	○	○
An AI chatbot could provide accurate and personalized recommendations for mental health. (COMP2)	○	○	○	○	○
I trust that an AI chatbot would offer effective solutions to support my mental well-being. (COMP3)	○	○	○	○	○

Q10 Intention to Use

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
I intend to use an AI chatbot for mental health support if it becomes available. (IU1)	○	○	○	○	○
I am likely to recommend an AI chatbot to others for managing their mental health. (IU2)	○	○	○	○	○
I would be willing to try an AI chatbot to support my mental well-being. (IU3)	○	○	○	○	○

End of Block: Default Question Block

Start of Block: Block 2

Q11 What is your gender?

- ◯ Male (1)
- ◯ Female (2)
- ◯ Non-binary (3)

Q12 What is your age?

- ◯ 18-21 (1)
- ◯ 22-25 (2)
- ◯ 26-30 (3)
- ◯ 31-35 (4)
- ◯ 36-40 (5)
- ◯ 41-50 (6)
- ◯ 50+ (7)

Q13 What is the highest level of education you have completed?

- Primary school (1)
- Middle school (2)
- High school (3)
- Bachelor's degree (4)
- Master's degree (5)
- Doctorate or PhD (6)

End of Block: Block 2

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa