USE OF AI CHATBOTS IN INFLUENCING MENTAL HEALTH STATUS AMONG UNIVERSITY UNDERGRADUATES IN BENIN CITY, EDO STATE

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MAY, 2026

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BEING A ONE YEAR PROJECT PRESENTED TO THE DEPARTMENT OF PUBLIC HEALTH AND COMMUNITY MEDICINE, SCHOOL OF MEDICINE, COLLEGE OF MEDICAL SCIENCES, UNIVERSITY OF BENIN, BENIN CITY, EDO STATE, NIGERIA

IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE AWARD OF BACHELOR OF MEDICINE AND BACHELOR OF SURGERY (MBBS) DEGREE IN THE UNIVERSITY OF BENIN, BENIN CITY, EDO STATE, NIGERIA.

MAY, 2026

DECLARATION

I hereby declare that this research project titled **"USE OF AI CHATBOTS IN INFLUENCING MENTAL HEALTH STATUS AMONG UNIVERSITY UNDERGRADUATES IN BENIN CITY, EDO STATE"** was carried out by HASSAN ABDULHAMEED OLUWASEYI with matriculation number MED1807408 under supervision of **Professor A. I. Obi** and has not been submitted in part or in full for any purpose.

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CERTIFICATION

This is to certify that this research study titled **"USE OF AI CHATBOTS IN INFLUENCING MENTAL HEALTH STATUS AMONG UNIVERSITY UNDERGRADUATES IN BENIN CITY, EDO STATE"** was conducted by HASSAN ABDULHAMEED OLUWASEYI with matriculation number MED1807408 under the supervision of Professor A. I. Obi. In the Department of Public Health and Community Medicine, College of Medical Sciences, University of Benin as part of the requirements for the award of Bachelor of Medicine, Bachelor of Surgery (MBBS) degree.

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DEDICATION

This work is dedicated first and foremost to Almighty Allah, whose mercy, guidance, strength, and favour made this journey possible.

To my beloved parents, Mr. and Mrs. Filani Taiwo Hassan, for their sacrifices, prayers, encouragement, and unwavering support throughout the demanding years of medical training. This project is also dedicated to my siblings, Muizzah, Mubarak and Maruf, for their love, support, and encouragement throughout this journey.

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LIST OF ABBREVIATIONS

ACHA: American College Health Association

AI: Artificial Intelligence

CBT: Cognitive Behavioral Therapy

CMDs: Common Mental Disorders

DSM-5: Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition

e-Health: Electronic Health

GAD-7: Generalized Anxiety Disorder-7 Scale

GST: General Studies

ICT: Information and Communication Technology

JMIR: Journal of Medical Internet Research

LMICs: Low- and Middle-Income Countries

NUC: National Universities Commission

OR: Odds Ratio

PHQ-9: Patient Health Questionnaire-9

SPSS: Statistical Package for the Social Sciences

UAE: United Arab Emirates

UNIBEN: University of Benin

UTAUT: Unified Theory of Acceptance and Use of Technology

WHO: World Health Organization

DEFINITION OF TERMS

Artificial Intelligence (AI): The simulation of human intelligence processes by computer systems, enabling machines to perform tasks that typically require human cognition, such as learning, reasoning, problem-solving, and natural language understanding.

AI Chatbot: A computer program that uses artificial intelligence and natural language processing to simulate human conversation through text-based or voice-based interaction, enabling automated responses to user inputs in real time.

Mental Health: A state of well-being in which an individual recognizes their own potential, effectively manages everyday stressors, maintains productivity, and actively participates in their community, as defined by the World Health Organization.

Depression: A common mental health disorder characterized by persistent low mood, loss of interest or pleasure in activities, fatigue, feelings of worthlessness, difficulty concentrating, sleep disturbances, and in severe cases, thoughts of self-harm or suicide. In this study, depression was assessed using the Patient Health Questionnaire-9 (PHQ-9), with a score of ≥ 5 used as the screening cut-off for probable depression.

Knowledge: In the context of this study, knowledge refers to the respondent's awareness, understanding, and factual information regarding the existence, capabilities, therapeutic applications, and limitations of AI chatbots specifically designed for mental health support.

Attitude: The respondent's psychological predisposition or disposition toward the acceptability, usefulness, and trustworthiness of AI chatbots as a tool for mental health support. Attitude was assessed using a 3-point Likert scale and classified as positive or negative based on the mean score obtained.

Uptake: The act of having ever used an AI chatbot at least once, regardless of purpose or frequency. In this study, uptake was operationalized as a binary variable – users versus non-users – based on self-reported lifetime use.

Level of Utilization: The regularity and frequency with which a respondent actively engages with AI chatbots. In this study, respondents were classified as high or low users based on their reported frequency of use, with high utilization defined as using AI chatbots "Often" or "Very Often."

Dependency: A pattern of AI chatbot engagement characterized by psychological indicators including preoccupation with use, tolerance, escapism, failed attempts to reduce use, withdrawal-like restlessness when unable to access the tool, and negative impact on academic or social functioning. Dependency was assessed using a 6-item Likert scale with a composite score ranging from 6 to 30, and dichotomized into low dependency (score 6–20) and high dependency (score 21–30) for analytical purposes.

Digital Mental Health: The use of digital technologies, including mobile applications, online platforms, and artificial intelligence tools, to deliver, support, or enhance mental health interventions, psychoeducation, and psychological support services.

Digital Literacy: The ability to access, navigate, evaluate, and use digital technologies effectively and safely. In the context of this study, digital literacy refers specifically to a student's familiarity with and confidence in using AI-based tools and platforms.

Facilitating Conditions: The organizational, technical, and infrastructural factors that support or enable a user to engage with a technology. In this study, facilitating conditions include access to smartphones, internet connectivity, affordable data subscriptions, and reliable electricity supply.

Social Influence: The degree to which an individual perceives that significant others – such as peers, friends, or lecturers – believe they should use a particular technology. Social influence was assessed in this study through peer encouragement and awareness of peer AI chatbot use.

Perceived Usefulness: The degree to which a student believes that using an AI chatbot would enhance their ability to manage their mental well-being and address psychological distress effectively.

Perceived Ease of Use: The degree to which a student believes that interacting with an AI chatbot would require minimal cognitive effort and would be straightforward to navigate.

Anonymity: The condition in which a user's identity and personal information remain unknown or undisclosed during interaction with an AI chatbot, thereby reducing the risk of social judgment or stigma associated with seeking mental health support.

Mental Health Stigma: Negative attitudes, beliefs, and social discrimination directed toward individuals experiencing mental health challenges, which may discourage help-seeking behaviour and limit engagement with available support services.

PHQ-9 (Patient Health Questionnaire-9): A validated nine-item self-report screening instrument used to assess the presence and severity of depressive symptoms over the preceding two weeks. In this study, the PHQ-9 was used as the primary instrument for assessing respondents' current mental health status.

Undergraduate Student: A student enrolled in a first-degree programme at a university or tertiary institution who has not yet obtained a bachelor's degree.

ABSTRACT

BACKGROUND

Mental health disorders among university students are an increasing public health concern globally, particularly in low- and middle-income countries where access to formal mental health services remains limited. Simultaneously, artificial intelligence (AI) chatbots are increasingly being integrated into students' academic and social activities, with emerging interest in their potential role in mental health support. This study aimed to assess the knowledge, attitudes, uptake, utilization, factors influencing use, and mental health status associated with AI mental health chatbot use among undergraduate students of the University of Benin, Benin City, Edo State, Nigeria.

METHODS

An analytical cross-sectional study was conducted among 436 undergraduate students of the University of Benin, Benin City, Edo State, Nigeria, using a pretested self-administered structured questionnaire. Respondents were selected using a multistage sampling technique. Data collected were analyzed using IBM SPSS version 25.0. Statistical significance was set at $p < 0.050$ at 95% confidence interval.

RESULTS

The mean age of respondents studied was 21.84 ± 3.97 years. Nearly all respondents demonstrated awareness of AI chatbots, while approximately nine-tenths had good overall knowledge. However, awareness of clinically validated mental health–specific chatbots such as Woebot and Wysa was very low. About three-quarters of respondents demonstrated positive attitudes towards AI mental health chatbots. Uptake of AI chatbots was near-universal (96.6%), driven predominantly by general-purpose platforms such as ChatGPT for academic purposes. Uptake of clinically validated mental health-specific chatbots such as Woebot and Wysa was negligible. Only a small proportion reported using AI chatbots specifically for emotional support or mental health-related purposes.

Ethnicity and level of study were identified as significant predictors of good knowledge of AI chatbots. Respondents with good knowledge had significantly higher odds of positive attitudes towards AI mental health chatbots (OR = 4.003; CI = 1.940–8.258; $p < 0.001$). Peer influence, anonymity, affordability, and privacy concerns significantly influenced AI chatbot utilization. High utilization was significantly associated with academic level and religion.

Nearly three-fifths (59.9%) of respondents screened positive for depression. High AI chatbot utilization (OR = 1.753; CI = 1.083–2.836; $p = 0.022$) and high dependency (OR = 2.173; CI = 1.039–4.542; $p = 0.039$) were identified as significant predictors of depression.

CONCLUSION

Despite high awareness, positive attitudes, and near-universal uptake of AI chatbots among undergraduate students, awareness of clinically validated mental health–specific platforms remain low. Depression was highly prevalent among respondents, and high AI chatbot utilization and dependency were significantly associated with depressive symptoms. There is need for targeted digital mental health literacy programmes, institutional regulation of AI mental health tools, and integration of safe, evidence-based digital mental health interventions within university settings.

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND TO THE STUDY

Mental health, as defined by the World Health Organization, is a state of well-being in which individuals recognize their potential, effectively manage everyday stressors, maintain productivity, and actively participate in their communities.[1] Mental health issues among university students are increasingly acknowledged as a significant global public health concern. Campuses worldwide are witnessing a surge in cases of depression, anxiety, stress, and other psychological disorders. The World Health Organization reports that around one in seven young individuals aged 10–19 faces mental health challenges, which profoundly affect their education, social connections, and overall quality of life.[2] University students are particularly susceptible to these challenges, as they navigate the demands of academic pressure, financial burdens, social isolation, and the significant life transitions that often accompany their studies.

Although awareness of mental health issues is increasing, many university students hesitate to use traditional mental health services. This reluctance often stems from societal stigma, a shortage of counselling professionals, financial constraints, and worries about maintaining confidentiality.[3] These obstacles have sparked a growing interest in innovative, technology-driven solutions. Among them is the advent of Artificial Intelligence (AI) chatbots – sophisticated conversational agents designed to offer psychological support, deliver cognitive behavioural therapy (CBT) modules, and enable emotional tracking through interactive, text-based conversations.[4]

AI chatbots are increasingly regarded for their accessibility, confidentiality, and round-the-clock availability, making them particularly appealing to young individuals who may shy away from traditional, in-person therapy. Platforms such as Woebot, Wysa, and Tess have been the focus of numerous studies demonstrating encouraging results in alleviating symptoms of depression, anxiety, and stress, representing a promising step toward bridging the gap in mental health care for underserved populations.[5,6] Despite these advancements, a significant gap remains in understanding undergraduates' knowledge, attitudes, and actual usage of these tools, particularly in low- and middle-income countries.

Understanding students' level of knowledge and attitudes toward AI chatbots is essential, as these factors significantly shape their willingness to adopt and engage with digital mental health solutions. Although many students are aware of AI-based tools, widespread misconceptions about their reliability and effectiveness often act as barriers to use.[7] Evaluating the extent to which students use AI chatbots can further shed light on how well these tools have been integrated into their daily self-care practices, with perceived utility, accessibility, cultural norms, and digital familiarity playing crucial roles.[8] Students experiencing significant psychological distress may also be more inclined to engage with AI-based support systems, making an assessment of their mental health status essential for understanding demand and guiding tool development.[9] Various factors – including technological proficiency, trust in AI, privacy concerns, social dynamics, and prior experience – further influence adoption and sustained use, and must be understood if the potential of AI chatbots is to be realized in university settings.[10]

In the Nigerian context, these challenges are particularly acute. Nigerian university students face a compounding of academic pressures, financial strain, and limited access to formal mental health services, within an environment characterized by significant mental health stigma and a critical shortage of mental health professionals.[11,12] Despite the rapid expansion of digital technology use among Nigerian youth, the integration of AI-driven mental health tools into university settings remains largely unexplored, and evidence on students' knowledge, attitudes, and utilization of such tools is scarce.[13,14] This study is therefore positioned to address this evidence gap at the University of Benin – a major federal university in South-South Nigeria – and to generate locally relevant findings that can inform digital mental health policy and practice within Nigerian tertiary institutions.

1.2 STATEMENT OF THE PROBLEM

Mental disorders rank among the leading causes of disability worldwide, affecting a substantial proportion of the global population at any given time.[1] Recent data from the World Health Organization highlights a persistent global gap in the availability of essential mental health services.[15] Although the global median number of mental health workers has risen from 9 per 100,000 people in 2014 to 13 per 100,000 in 2020, this increase remains inadequate to address the escalating demand for mental health services.[16] The disparity in mental health resources is striking: developed nations such as Denmark, Italy, and Iceland report approximately 17 psychiatrists per 100,000 people,[17] while many low-income countries, including Benin Republic, Chad, and Liberia, struggle with fewer than one psychiatrist per 1,000,000 people.[18] In Nigeria, this crisis is similarly severe, with an estimated 0.1 psychiatrists per 100,000 population, leaving millions without access to specialist care.[12] These systemic shortages make it difficult to implement traditional one-on-one mental health interventions, particularly for populations such as university students who face heightened vulnerability to psychological distress.

Within this context of chronic resource scarcity, Artificial Intelligence chatbots have emerged as a potentially scalable, cost-effective, and stigma-reducing approach to bridging the gap in mental health support. AI-driven chatbots are capable of delivering immediate emotional support, evidence-based cognitive behavioural interventions, and personalized psychoeducation at any hour, without the barriers of cost, availability, or social judgment that often deter students from seeking conventional care.[19] Their integration into university health systems therefore represents an important frontier in addressing the growing mental health burden among undergraduates.

However, the effective deployment of AI chatbots in any setting is contingent upon adequate knowledge, favourable attitudes, and meaningful utilization among the target population. In the Nigerian context, little is known about how much students actually know about AI chatbot technology and its mental health applications. Limited awareness or functional understanding may hinder effective utilization of such tools.[13] Furthermore, students' attitudes toward AI-powered mental health solutions – encompassing trust in technology, perceived usefulness, and concerns about privacy and empathy – may greatly influence adoption rates.[8] The adoption and sustained use of AI chatbots are additionally shaped by factors such as technological literacy, peer influence, infrastructural constraints, cost, and cultural acceptability, none of which have been adequately characterized among Nigerian university students.[10,14]

Therefore, this study seeks to address this evidence gap by assessing the knowledge, attitudes, utilization patterns, and mental health status of undergraduate students at the University of Benin in relation to AI chatbot use, and by identifying the key individual, social, and structural factors that influence their engagement with these tools. The findings are intended to contribute to evidence-based strategies for integrating digital mental health interventions within Nigerian tertiary institutions.

1.3 JUSTIFICATION

Despite the growing global burden of mental health disorders among university students, access to timely and effective mental health support remains critically limited, particularly in low- and middle-income countries such as Nigeria where professional mental health resources are severely scarce and stigma remains a significant deterrent to help-seeking. AI-driven chatbots have emerged as a potentially scalable and stigma-reducing complement to conventional mental health services, offering round-the-clock availability, anonymity, and cost-effective support. However, the successful implementation of these tools is contingent upon adequate knowledge, favourable attitudes, and meaningful engagement among the intended users – none of which have been comprehensively assessed among undergraduate students in Nigeria.

Assessing students' knowledge of AI chatbots as a mental health tool is a necessary first step. Without a foundational understanding of these tools – their existence, capabilities, and limitations – students cannot make informed decisions about their use for psychological support. Evidence from Nigerian and African university settings suggests that while general awareness of AI is growing, specific knowledge of AI mental health applications remains limited, representing a critical gap that must be addressed before any institutional deployment can be considered. This study provides the first systematic assessment of this knowledge gap among students at the University of Benin, Nigeria's largest federal university in the South-South geopolitical zone.

Equally important is an understanding of students' attitudes toward AI chatbots for mental health support. Positive attitudes – shaped by perceived trust, utility, and anonymity – are essential drivers of technology adoption, while skepticism, fear of data breaches, and preference for human interaction serve as significant barriers. In the Nigerian context, where cultural and religious values may shape perceptions of machine-delivered emotional support in distinct ways, characterizing attitudinal patterns is particularly relevant for designing culturally acceptable implementation strategies. No prior study has examined these attitudinal dimensions specifically among UNIBEN undergraduates.

Characterizing the actual level of AI chatbot utilization among students is equally essential. Although AI tools are increasingly embedded in students' academic routines, their use for mental health purposes remains poorly understood, particularly in sub-Saharan African university settings. Understanding whether students use these tools for emotional support, and under what circumstances, is necessary for identifying gaps in uptake and for informing institutional strategies to promote safe and purposeful engagement.

A concurrent assessment of students' mental health status is also justified, as the prevalence and severity of depressive symptoms within the population determines the urgency and relevance of AI chatbot-based interventions. Evidence from Nigerian tertiary institutions indicate a substantial burden of depression and anxiety among undergraduates, with low rates of formal help-seeking. Establishing the current mental health profile of UNIBEN students provides the epidemiological foundation necessary to contextualize patterns of AI chatbot use and dependency observed in this study.

Finally, identifying the individual, social, and structural factors that facilitate or hinder AI chatbot use is critical for translating research findings into actionable policy. In a Nigerian setting characterized by infrastructural limitations, high data costs, mental health stigma, and strong peer influence dynamics, understanding these determinants is essential for designing effective digital mental health programmes. The findings of this study will therefore provide evidence to guide the University of Benin management, the National Universities Commission, and the Federal Ministry of Health in developing targeted strategies for integrating AI-driven mental health tools into Nigerian university health systems in a safe, equitable, and evidence-based manner.

1.4 RESEARCH QUESTIONS

This study addressed five research questions.

1. What is the level of knowledge of undergraduate students about the use of AI chatbots for mental health support?
2. What are the attitudes of undergraduate students towards the use of AI chatbots in supporting mental health?
3. To what extent are AI chatbots being used by undergraduate students in relation to mental health support?
4. What is the current mental health status of undergraduate students in the study population?
5. What factors influence the use of AI chatbots for mental health support among undergraduate students?

1.5 AIMS AND OBJECTIVES

General Objectives

To assess the use of AI chatbots in influencing mental health among undergraduate students in Benin City for the purpose of improving mental health and overall well-being.

Specific Objectives

1. To assess the level of knowledge of AI chatbot use in relation to mental health among University of Benin students.
2. To ascertain the attitudes of University of Benin students toward the use of AI chatbots for mental health support.
3. To determine the level of AI chatbot usage by University of Benin students in addressing mental health concerns.
4. To identify the current mental health status of University of Benin students.
5. To determine the factors influencing the use of AI chatbots for mental health support among University of Benin students.

CHAPTER TWO

LITERATURE REVIEW

2.1 BACKGROUND

Mental health has emerged as a critical global public health concern, disproportionately affecting young people and university students. The transition to higher education frequently brings substantial psychological challenges, including academic demands, social integration difficulties, financial pressures, and identity development stressors, all of which increase vulnerability to depression, anxiety, and related disorders.[3,20] The World Health Organization estimates that approximately one in seven young people aged 10 to 19 years experiences a mental health disorder, with suicide now representing the fourth leading cause of death among individuals aged 15 to 29 globally.[2] Despite this growing burden, access to conventional mental health services remains critically limited, particularly in low- and middle-income countries where the mental health workforce is severely inadequate, with a global median of just 13 mental health workers per 100,000 people.[21] Even in better-resourced settings, stigma, confidentiality concerns, and prolonged waiting times frequently deter students from pursuing traditional care.[10]

In response to these systemic gaps, Artificial Intelligence chatbots have emerged as a promising scalable, stigma-free, and cost-effective complement to conventional mental health services. These automated conversational agents are designed to deliver emotional support, cognitive behavioural therapy modules, mood tracking, and psychoeducation through accessible, text-based interaction, with the distinctive advantages of 24/7 availability, anonymity, and personalization.[4] However, while the potential of AI chatbots in mental health support has attracted growing research interest globally, evidence on students' knowledge, attitudes, utilization patterns, and the contextual factors shaping engagement – particularly within Nigerian and sub-Saharan African university settings –

remains sparse. This chapter reviews the existing literature across these dimensions to identify the gaps that the present study is positioned to address.

2.2 THEORETICAL FRAMEWORK

The theoretical foundation of this study is anchored on a triangulation of three complementary frameworks: the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology Acceptance Model (TAM), and the Health Belief Model (HBM). This multi-theoretical approach provides a robust lens for understanding the complex interplay between technological adoption and health-seeking behaviour among university students.

2.2.1 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was originally developed by Venkatesh et al. as a comprehensive model for explaining user intentions to utilize an information system and the subsequent usage behaviour. The model consolidates constructs from eight prior technology acceptance theories into four key determinants of adoption: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. In the context of this study, the UTAUT framework has been applied as adapted for health technology settings by Tao et al. and Mosleh et al.[22,23]

Performance Expectancy refers to the degree to which an individual believes that using a system will help them attain gains in performance – in this context, the belief that an AI chatbot will effectively support their mental well-being. Effort Expectancy refers to the perceived ease associated with using the system. Social Influence reflects the extent to which an individual perceives that significant others – such as peers or lecturers – believe they should use the technology. Facilitating Conditions refer to the user's belief that an organizational and technical infrastructure exists to support the system's use, encompassing factors such as internet connectivity, device access, and institutional support.[22,23]

2.2.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model was originally proposed by Davis as a framework explaining the pathways through which users come to accept and use a technology. TAM posits that two specific beliefs are the primary determinants of an individual's attitude toward using a system: Perceived Usefulness and Perceived Ease of Use. In this study, TAM is applied as utilized by Luo et al. in the context of AI mental health chatbot acceptance.[7]

Perceived Usefulness refers to the degree to which a student believes that using an AI chatbot would enhance their ability to manage their mental well-being. Perceived Ease of Use refers to the degree to which a student believes that interacting with the chatbot would require minimal cognitive effort. Together, these two constructs determine the student's attitude toward the technology, which in turn influences their behavioural intention to use it.[7]

2.2.3 Health Belief Model (HBM)

The Health Belief Model is a psychological health behaviour change framework originally developed by Rosenstock and subsequently expanded by Becker, widely applied in public health research to explain and predict health-related behaviours. In this study, the HBM is applied as utilized by Rackoff et al. in the context of digital mental health engagement.[9]

The HBM posits that an individual's willingness to engage in a health behaviour – such as using an AI chatbot for mental health support – is determined by five key perceptual constructs:

Perceived Susceptibility, referring to one's assessment of personal risk of experiencing a mental health condition; Perceived Severity, referring to one's belief about the seriousness of that condition; Perceived Benefits, referring to the belief that using an AI chatbot would effectively reduce that risk or distress; Perceived Barriers, referring to the psychological and practical costs of engagement, such as privacy fears or distrust of automated systems; and Cues to Action, referring to triggers that activate readiness to use the tool, such as acute exam stress or a peer's recommendation.[9]

2.3 CONCEPTUAL FRAMEWORK

The conceptual framework of this study explains how knowledge and attitude shape the uptake and level of utilisation of AI chatbots for mental health support among University of Benin undergraduates, while recognising that this adoption pathway is constrained or enabled by a constellation of individual, technological, and environmental factors.[22,23]

Core constructs and outcome pathways

1. Knowledge of AI chatbots in mental health constitutes the foundational input construct of the framework. It encompasses awareness of specific AI tools available for psychological support – such as ChatGPT, Wysa, and Woebot – as well as an understanding of their therapeutic capabilities, including delivery of CBT techniques, mood tracking, and emotional regulation support, and their limitations, including the fact that they are not human therapists and cannot prescribe medication.[13,24] Consistent with the UTAUT Performance Expectancy construct, adequate knowledge is expected to increase the likelihood of initial experimentation with AI tools and to promote safer, more purposeful utilisation.[9]

2. Attitude toward AI chatbot use represents the psychological mediator between knowledge and behavioural intent. In the mental health context, student attitudes are heavily shaped by perceived anonymity – the degree to which the tool is seen as a stigma-free, non-judgmental space for emotional disclosure – as well as perceived empathy and trust in the technology's ability to provide meaningful support.[7,25] Consistent with the TAM framework, positive attitudes driven by perceived usefulness and ease of use are expected to predict higher uptake, while negative attitudes driven by distrust, fear of robotic interaction, or concerns about data privacy serve as barriers to engagement.[7,26]
3. Uptake – defined as whether the student has ever used an AI chatbot during a period of stress or emotional distress – represents the first threshold of the adoption pathway. It is operationalized as a binary outcome and serves as the gateway variable through which knowledge and attitude translate into behaviour. Uptake is often triggered by immediate situational need, such as acute exam stress or social anxiety, but does not in itself guarantee sustained or purposeful use.[9,23]
4. Level of utilisation represents the depth and regularity of engagement beyond initial uptake. It captures the intensity of interaction – including frequency of use, average daily hours, and the specific purpose of engagement, whether for deep emotional support or incidental academic use – and constitutes the primary behavioural outcome of the adoption process.[22] High-level utilisation is expected among students who combine adequate knowledge, positive attitudes, and favourable facilitating conditions.[22]

Determinant domains (influencing factors)

The pathway from knowledge and attitude to uptake and utilization is moderated by three domains of influencing factors, operationalized consistent with the UTAUT and HBM frameworks:

A. Individual factors

- Student's current mental health status, assessed using the PHQ-9, which determines the perceived susceptibility and severity constructs of the HBM. Students experiencing higher levels of psychological distress may be more motivated to seek support via AI chatbots due to their non-judgmental and immediately accessible nature.[9,26]
- Digital literacy – encompassing prior experience with digital tools and confidence in navigating technology – additionally shapes willingness to experiment with AI-based interventions.[14,27]

B. Technology-related factors

- Perceived Privacy/Anonymity: Perceived privacy and anonymity represents a critical driver particularly in stigma-sensitive contexts. The perception that AI interaction is confidential and invisible to peers and family members is a powerful facilitator of uptake among students who would otherwise avoid formal mental health services.[7,25]
- Trust and Reliability: Concerns about algorithmic reliability, data security, and the risk of receiving inaccurate emotional guidance constitute significant technological barriers to adoption.[28,29]

C. Environmental/Contextual factors

- Stigma: Stigma, operating at both the campus and societal level, exerts a dual influence – discouraging formal help-seeking while simultaneously encouraging the use of private digital alternatives.[7,25]

- Infrastructure (Facilitating Conditions): Facilitating conditions – including data affordability, device ownership, internet reliability, and electricity supply – represent the physical infrastructure through which intent is converted into actual use, and constitute a particularly significant moderating domain in the Nigerian university context.[14,27]

Mediators and moderators

- Trust operates as a key mediator along the adoption pathway. Adequate knowledge reduces misconceptions about AI capabilities, thereby building trust and lowering the perceived barrier of engaging with a non-human support system. Conversely, privacy concerns erode trust and suppress utilization even among students who have already achieved initial uptake.[7,29]
- Facilitating conditions operate as a moderator of the full pathway: a student may possess strong knowledge, positive attitudes, and genuine psychological need, yet without reliable internet access and affordable data, utilization cannot be sustained regardless of intent.[14]

2.4 APPLICATION OF THEORIES TO CURRENT STUDY

Integrating these three theoretical frameworks provides a holistic lens for addressing each of the study's five specific objectives. Each theory is applied to the objective it most directly illuminates, while recognizing that the frameworks are complementary and that their constructs interact across objectives.

The UTAUT framework is applied to Objective 1 (Knowledge of AI Chatbots). Performance Expectancy – the belief that using an AI chatbot will effectively support one's mental well-being – is contingent upon the student first possessing adequate knowledge of the tool's existence, purpose, and capabilities. A student who is unaware of what AI chatbots can do cannot form a meaningful performance expectancy. This study therefore treats knowledge as the foundational prerequisite through which UTAUT's Performance Expectancy construct becomes operationalisable.[22,23]

The Technology Acceptance Model (TAM) is applied to Objective 2 (Attitudes Towards AI Chatbots). TAM posits that Perceived Usefulness and Perceived Ease of Use are the primary determinants of a user's attitude toward a technology.[7] In the context of this study, a student's attitude toward using AI chatbots for mental health support is shaped by whether they perceive these tools as genuinely helpful for emotional regulation and as sufficiently simple to navigate without specialized technical skills. These attitudinal constructs directly predict behavioural intention to use the technology.[7]

The UTAUT framework is additionally applied to Objective 3 (Level of AI Chatbot Utilization) and Objective 5 (Factors Influencing Use). Facilitating Conditions – encompassing internet connectivity, data affordability, device access, and institutional support – determine whether a student who holds positive attitudes and adequate knowledge can translate that intent into actual utilization. Social Influence, particularly the role of peer recommendation and the stigma surrounding mental health help-seeking, further mediates the transition from intent to use.[32,33] Together, these constructs explain both the level of utilization observed and the structural and social factors that facilitate or impede it.

The Health Belief Model (HBM) is applied to Objective 4 (Current Mental Health Status). The HBM posits that engagement with a health behaviour is driven by the individual's perception of their own susceptibility to and the severity of a health condition, weighed against the perceived benefits and barriers of the recommended action.[9] In this study, a student's current mental health status – as assessed by the PHQ-9 – serves as the empirical basis for their perceived susceptibility and severity. A student experiencing significant depressive symptoms may perceive a greater personal benefit from AI chatbot use, yet simultaneously face heightened perceived barriers such as distrust of automated emotional support or fear of data disclosure. The HBM thus explains why two students with equivalent knowledge and attitudes may make different decisions about AI chatbot engagement based on their current psychological state.[9]

Collectively, this triangulated framework accounts for the cognitive, attitudinal, behavioural, and health-related dimensions of AI chatbot adoption among university students, providing a theoretically grounded basis for the study's design, variable selection, and interpretation of findings.

2.5 LEVEL OF KNOWLEDGE OF UNDERGRADUATE STUDENTS ABOUT THE USE OF AI CHATBOTS FOR MENTAL HEALTH SUPPORT

The successful utilization of AI chatbots as a component of digital mental health support is inextricably linked to the awareness and functional understanding of the end-users. Knowledge in this context is defined as the student's awareness, understanding, and factual information concerning the operational capabilities, therapeutic applications, and limitations of AI tools specifically designed for mental health intervention.[23,24] Across diverse economic landscapes, a strong consensus exists that a user's knowledge is a prerequisite for realizing the benefits of digital health tools – high-quality utilization depends on a detailed understanding of the system's purpose, moving beyond simple generative tasks toward complex emotional self-regulation and crisis recognition.[9,30]

International studies consistently find that while undergraduates generally possess a baseline awareness of Artificial Intelligence, the depth of their functional health knowledge remains a critical determinant of successful adoption. Rackoff et al. conducted an evaluation among college students in the United States, revealing a significant knowledge-utilization paradox: while 49.0% of participants demonstrated instrumental knowledge of chatbots for general inquiries, only 5.0% possessed the specialized knowledge required to identify these tools as valid pathways for mental health support.[9] This therapeutic literacy gap is further corroborated by Abd-Alrazaq et al., whose systematic review highlighted that digital mental health interventions are significantly underutilised because students lack awareness of their evidence-based capabilities, such as the delivery of Cognitive Behavioural Therapy modules.[30] Collectively, these studies confirm that knowledge must be directly applicable to the digital therapeutic environment rather than being merely technical or academic in nature.[30]

In the African context, rising digital interest often coexists with a lack of structured educational exposure to AI mental health applications. Orok et al., in a study of pharmacy students at a Nigerian university, found that while awareness of AI tools was growing, specific knowledge of their mental health applications remained limited, with students demonstrating shallow familiarity that did not translate into purposeful engagement.[31] Furthermore, Nicolaidou et al. emphasized that the required knowledge encompasses not only basic digital skills but also an understanding of data security and privacy protocols within health applications, noting that surface-level familiarity frequently results in a failure to sustain long-term engagement with digital mental health tools.[32] This suggests that for AI chatbot adoption to be meaningful in African university settings, institutional interventions must transition students from general digital awareness to specialized functional proficiency in therapeutic AI applications.[32]

In the Nigerian context, the level of knowledge required must be robust enough to facilitate the integration of AI into daily student life despite significant implementation barriers. Suleiman et al., in their investigation of AI adoption across Nigerian universities, found that while students were increasingly familiar with AI applications in administrative and academic processes, their knowledge of specialized mental health applications remained minimal.[13] This disparity highlights that theoretical awareness of general AI concepts does not automatically translate into the functional literacy necessary to engage purposefully with clinical-grade chatbots.[13] Yusuf et al. further argued that for AI chatbots to be effectively integrated into the Nigerian university framework, students must first be adequately informed regarding their specific therapeutic capabilities and ethical limitations, noting that without targeted educational efforts, high general awareness will continue to be decoupled from practical mental health utilization due to persistent infrastructural and orientational challenges.[14]

In summary, the literature confirms that knowledge is a non-negotiable prerequisite for successful digital mental health adoption. While general AI awareness is growing among Nigerian university students, evidence consistently points to a gap between theoretical familiarity and the functional, health-specific knowledge required for purposeful chatbot engagement. To date, no published study has systematically assessed the depth of AI chatbot knowledge among undergraduate students at the University of Benin, representing a critical gap this study is positioned to address.[13,14,27]

2.6 ATTITUDES OF UNDERGRADUATE STUDENTS TOWARDS THE USE OF AI CHATBOTS IN MENTAL HEALTH SUPPORT

Attitude in the context of digital health refers to the predisposition or perception of individuals toward the acceptability, usefulness, and trustworthiness of a particular digital intervention. In relation to AI chatbots for mental health support, attitude encompasses students' willingness to engage with these tools as potential sources of emotional support, psychological guidance, and mental health information.[7,9] Positive attitudes toward digital mental health technologies are important because they strongly influence behavioural intention and eventual utilization. Similar to the adoption of other e-health innovations, favourable attitudes are often shaped by perceived usefulness, accessibility, privacy, and trust in the technology.[13,23]

International literature suggests that university students generally demonstrate cautiously positive attitudes toward AI chatbots for mental health support, although concerns regarding empathy, trustworthiness, and accuracy remain important limitations. Rackoff et al. reported that college students in the United States viewed AI chatbots as less effective than traditional face-to-face mental health services, yet still considered them useful as accessible and low-barrier support tools.[9] Students particularly valued the anonymity, convenience, and affordability associated with chatbot-based support, especially for managing stress-related concerns without fear of stigma.[9] Similarly, Tao et al. found that more than half of medical students in China expressed favourable attitudes toward chatbot-assisted mental health support, largely because such tools were perceived as non-judgmental and easily accessible.[23] However, concerns regarding misinformation, limited emotional depth, and uncertainty about the reliability of automated advice reduced complete confidence in AI systems.[23] In addition, Mosleh et al., in a study among university students in the United Arab Emirates, observed that students with greater emotional self-awareness and familiarity with digital technologies were more likely to exhibit positive attitudes toward chatbot use.[22]

Within African settings, attitudes toward AI-driven mental health support appear to be shaped by a combination of growing digital interest and persistent preference for human interaction. Existing evidence suggests that although direct engagement with mental health chatbots remains relatively low, many students demonstrate willingness to consider their use when informed about their potential benefits, particularly continuous availability and privacy protection.[9] However, concerns relating to interpersonal connection, cultural relevance, and technological trust continue to influence acceptability. These findings suggest that attitudes toward AI mental health support within African contexts are influenced not only by technological factors, but also by broader sociocultural perceptions regarding emotional support and help-seeking behaviour.

In the Nigerian university setting, attitudes toward AI chatbots may be influenced by the high burden of mental health stigma and the desire for confidential support channels. Suleiman et al. observed that Nigerian university students generally expressed favourable perceptions toward AI systems because of their responsiveness, accessibility, and convenience within academic settings.[13] The authors suggested that such perceptions may extend to mental health support applications, particularly in contexts where students experience barriers to formal counselling services. Furthermore, the perceived anonymity associated with AI chatbots may increase acceptability among students who are reluctant to openly discuss emotional or psychological concerns because of fear of stigma or social judgment.[13,25]

Local evidence from Benin City further suggests that positive perceptions toward digital health innovations do not always translate into actual utilization. Owoeye et al., among healthcare workers in Benin City, reported generally favourable attitudes toward e-health technologies but noted that infrastructural limitations, including unstable internet connectivity and inadequate technical support, significantly reduced practical implementation.[33] This suggests that while undergraduate students may perceive AI chatbots positively as accessible and private mental health support tools, actual acceptance and sustained engagement may still be influenced by broader structural challenges such as internet access, electricity supply, and digital literacy.

Overall, the literature indicates that undergraduate students generally hold moderately favourable attitudes toward AI chatbots for mental health support, particularly because of their accessibility, anonymity, and convenience. Nevertheless, concerns regarding empathy, misinformation, privacy, and infrastructural limitations continue to influence acceptance. To date, no known published study has systematically examined the attitudes of undergraduate students at the University of Benin toward the use of AI chatbots for mental health support. This represents an important knowledge gap which the present study seeks to address.

2.7 LEVELS OF UTILIZATION OF AI CHATBOTS FOR MENTAL HEALTH SUPPORT AMONG UNDERGRADUATE STUDENTS

Utilization refers to the actual use or engagement with AI chatbots for mental health-related purposes, including emotional support, stress management, mental health information seeking, mood monitoring, and coping assistance. It represents the behavioural outcome of awareness, knowledge, and attitudes toward digital mental health technologies.[9,23] Within the context of mental health support, utilization is important because it reflects the extent to which students are willing to incorporate AI-driven tools into their help-seeking and coping practices.

International evidence suggests that although undergraduate students widely utilize AI chatbots for academic, informational, and general productivity purposes, utilization specifically for mental health support remains comparatively limited.[9,23] Rackoff et al. reported a significant disparity among college students in the United States between general chatbot use and mental health-related engagement, with many students using AI tools for routine tasks while only a small proportion reported seeking emotional or psychological support through such platforms.[9] Even among students experiencing depressive symptoms, mental health-related utilization remained relatively low, suggesting that availability and accessibility alone may not necessarily translate into mental health use.[9] Similarly, Mosleh et al. observed that university students in the United Arab Emirates frequently used chatbots for academic activities, but utilization for health-related purposes was substantially less common.[22] The authors suggested that concerns regarding trust, emotional depth, and perceived clinical reliability may contribute to this pattern.[22]

Evidence from low- and middle-income settings suggests that utilization of AI chatbots for mental health support remains at an emerging stage.[9,32] Studies indicate that although digital infrastructure and awareness of AI technologies are gradually increasing, actual engagement with mental health-specific chatbot platforms remains limited. Existing literature suggests that utilization is often influenced by availability of institutional support, digital literacy, and user confidence in the effectiveness of such technologies.[29,32] In addition, interactive design, user engagement features, and perceived responsiveness have been identified as important determinants of sustained utilization.[32] Furthermore, in a quasi-experimental study, Kim et al. observed that consistent engagement with AI-assisted support platforms was associated with improved psychological outcomes, particularly reductions in loneliness among frequent users.[26] This finding highlights the importance of regular and sustained utilization in achieving meaningful mental health benefits.

Within the Nigerian context, utilization of AI chatbots for mental health support remains relatively underexplored and appears to be overshadowed by more common academic and administrative applications of AI technologies.[13,14] Suleiman et al. observed that while Nigerian university students increasingly utilize AI systems for learning activities, assignments, and information retrieval, structured utilization for mental health support has not yet been formally integrated into most tertiary institutions.[13] Consequently, current engagement with AI chatbots for emotional or psychological support is likely to remain largely informal, self-directed, and inconsistent. Yusuf et al. further identified infrastructural barriers such as unstable internet connectivity, unreliable electricity supply, and high data costs as important constraints limiting sustained utilization of digital health technologies in Nigeria.[14,27] These challenges may significantly reduce the practicality of continuous AI chatbot engagement despite positive perceptions toward such tools.

Overall, available literature suggests that utilization of AI chatbots for mental health support among undergraduate students remains relatively low when compared with general AI use. Although awareness and acceptance of AI technologies are increasing globally and within Nigeria, sustained engagement for mental health-related purposes appears to be limited by concerns regarding trust, digital literacy, infrastructural barriers, and lack of institutional integration. Furthermore, no published study to the best of the researcher's knowledge has specifically examined the level of utilization of AI chatbots for mental health support among undergraduate students at the University of Benin. This represents an important gap which the present study seeks to address.

2.8 MENTAL HEALTH STATUS OF UNDERGRADUATE STUDENTS

Mental health status among undergraduate students is an important determinant of academic performance, social functioning, and overall quality of life. In this study, mental health status is considered primarily in relation to common mental disorders such as depression and anxiety, which constitute a substantial proportion of psychological morbidity among young adults.[15,18] Assessing the mental health status of students is particularly important because university life is often associated with multiple stressors including academic demands, financial challenges, social adjustment difficulties, and uncertainty regarding future career prospects.[19] Understanding the burden of psychological distress among undergraduates is therefore essential in evaluating the potential role of AI chatbots and other digital mental health interventions as supportive tools within university settings.

Globally, there has been growing concern regarding the increasing prevalence of mental health problems among university students. The WHO World Mental Health Surveys International College Student Project, led by Auerbach et al., reported that approximately one-third of students across multiple countries met criteria for at least one mental disorder within a 12-month period, with depressive and anxiety disorders being among the most common conditions identified.[20] Similarly, reports from the American College Health Association indicated that a large proportion of undergraduate students experienced moderate to severe psychological distress, including depressive symptoms severe enough to impair daily functioning and academic activities.[3] These findings highlight the substantial mental health burden among university students worldwide and emphasize the limitations of traditional mental health systems in adequately meeting the growing demand for psychological support services.

Within low- and middle-income countries, the mental health burden among undergraduate students is further compounded by socioeconomic challenges, limited mental health infrastructure, and inadequate access to professional support services.[18] McKenzie et al. and related regional studies observed that students in these settings frequently experience combined pressures arising from academic stress, financial hardship, and social instability, all of which contribute to increased vulnerability to depression and anxiety.[18] In many African countries, access to mental health services remains limited, with available resources often concentrated on severe psychiatric disorders rather than common psychological conditions affecting students and young adults.[18] Consequently, many students experiencing emotional distress remain undiagnosed and untreated, thereby increasing the risk of poor academic performance, social dysfunction, and reduced wellbeing.

The Nigerian university environment presents additional stressors that may adversely affect student mental health. Studies conducted among Nigerian undergraduates have consistently reported considerable levels of depression, anxiety, and psychological distress associated with academic workload, financial constraints, uncertain career prospects, and poor access to mental health services.[13,14] Furthermore, stigma surrounding mental illness continues to discourage many students from seeking professional psychological support.[11] Ogundipe et al. reported that although many Nigerian students experience significant emotional distress, only a small proportion seek formal help because of fear of stigmatization, lack of awareness, and limited confidence in available support systems.[11] These findings suggest that psychological distress among Nigerian undergraduates may often remain hidden or underreported despite its substantial impact on wellbeing and academic functioning.

Infrastructural limitations within many Nigerian tertiary institutions may also contribute indirectly to poor mental health outcomes. Challenges such as unstable electricity supply, inadequate accommodation, financial strain, and inconsistent internet access may worsen stress levels and reduce coping capacity among students.[14,27] In addition, students in senior academic levels may experience heightened psychological pressure because of examinations, research demands, and concerns regarding post-graduation opportunities.[14,27] Collectively, these factors contribute to a university environment in which emotional distress and depressive symptoms may become increasingly prevalent.

Overall, existing literature demonstrates that undergraduate students constitute a psychologically vulnerable population with a considerable burden of depression, anxiety, and related forms of distress globally and within Nigeria. Despite increasing recognition of student mental health challenges, access to adequate psychological support services remains limited in many university settings. Furthermore, no known published study has specifically assessed the mental health status of undergraduate students at the University of Benin in relation to AI chatbot engagement for mental health support using standardized assessment tools. This represents an important gap which the present study seeks to address.

2.9 FACTORS INFLUENCING THE USE OF AI CHATBOTS FOR MENTAL HEALTH SUPPORT AMONG UNDERGRADUATE STUDENTS

The use of AI chatbots for mental health support among undergraduate students is influenced by a complex interaction of individual, social, technological, and structural factors. These factors may either facilitate or hinder the adoption and sustained utilization of digital mental health interventions.[7,13] Understanding these determinants is important because the effectiveness of AI-based mental health support depends not only on the availability of the technology, but also on the willingness and ability of students to engage with it.[10,14]

Globally, studies have identified perceived usefulness, accessibility, convenience, and ease of use as major facilitators of AI chatbot adoption among university students. Rackoff et al. reported that students in the United States were more likely to engage with AI chatbots when they perceived them as helpful, easy to navigate, and capable of providing rapid responses to emotional concerns.[9]

The availability of round-the-clock support and the absence of appointment-related barriers were also identified as important motivators for utilization.[9] However, several barriers were equally reported, particularly concerns regarding lack of human empathy, limited emotional understanding, and uncertainty about the reliability of AI-generated advice.[9] Similarly, Tao et al. found that privacy concerns, data security fears, and ethical uncertainties significantly influenced willingness to utilize AI chatbots among medical students in China.[23] Students who expressed lower confidence in the trustworthiness and safety of AI systems were less likely to engage with such technologies for mental health purposes.[23] Collectively, these findings suggest that successful adoption of AI chatbots depends not only on technological functionality, but also on user trust and confidence in the system.

In low- and middle-income settings, factors influencing utilization appear to extend beyond individual perceptions to include broader socioeconomic and technological realities. Nicolaidou et al. observed that interactive design features, user engagement mechanisms, and perceived responsiveness significantly influenced continued use of mental health applications among young adults.[32] Applications perceived as impersonal, repetitive, or lacking conversational depth were more likely to be abandoned by users.[32] Furthermore, digital literacy has consistently emerged as an important determinant of AI engagement.[9,32] Students with limited ICT skills or poor confidence in using digital technologies may experience difficulty navigating AI platforms, thereby reducing utilization. These findings suggest that institutional support strategies may need to include digital literacy training in addition to merely introducing technological platforms.

Within the Nigerian context, several contextual factors may uniquely shape the use of AI chatbots for mental health support. Mental health stigma remains an important determinant of help-seeking behaviour among Nigerian students, making anonymity and confidentiality particularly attractive features of AI-driven support systems.[13] Suleiman et al. observed that students were more likely to accept AI-based systems when such platforms allowed private interaction without fear of social judgement or stigmatization.[13] The anonymous nature of AI chatbots may therefore encourage students who would otherwise avoid traditional counselling services to seek some form of psychological support. However, infrastructural limitations remain major barriers to sustained engagement. Yusuf et al. and Jibrin et al. identified unstable internet connectivity, unreliable electricity supply, inadequate technical support, and high data costs as major constraints limiting digital technology utilization in Nigeria.[14,27] These structural barriers may significantly reduce the practicality and consistency of AI chatbot use despite favourable attitudes toward such tools.

Evidence from Benin City similarly suggests that technological acceptance alone may not guarantee effective utilization. Owoeye et al. reported that although healthcare workers demonstrated positive perceptions toward e-health innovations, inadequate technical support, insufficient digital skills, and infrastructural instability negatively affected implementation and sustained use.[33] This suggests that for undergraduate students within the University of Benin environment, effective engagement with AI chatbots for mental health support may depend on whether the perceived benefits of anonymity, accessibility, and convenience can outweigh the structural barriers associated with the Nigerian digital environment.[11,33]

Overall, the literature indicates that the use of AI chatbots for mental health support among undergraduate students is influenced by multiple interconnected factors including perceived usefulness, anonymity, trust, privacy concerns, digital literacy, infrastructural reliability, and social stigma. While several studies have examined these determinants in international and broader Nigerian contexts, no published study has specifically quantified the factors influencing the uptake and utilization of AI chatbots for mental health support among undergraduate students at the

University of Benin. This represents an important knowledge gap which the present study seeks to address.

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CHAPTER THREE

MATERIALS AND METHODS

3.1 STUDY AREA

This study was conducted in the University of Benin, Edo State, Nigeria. Edo State is one of the 36 states in Nigeria and its capital is Benin City. It is situated in the South-South geopolitical zone of Nigeria. Its ethnic groups include Benin, Esan, Etsako, Owan and other tribes that reside in the state. Seven (7) universities are domiciled in the state comprising one federal university, two state and four private universities.[34]

The University of Benin is a federally owned university located in the Ovia North-East Local Government Area of Edo State. Founded in 1970 as an Institute of Technology, it was upgraded to a full-fledged university by the National Universities Commission on July 1, 1971. The institution transitioned from state to federal ownership on April 1, 1975.[34]

The University of Benin operates across two distinct campuses: the Ugbowo campus and the Ekenwan campus. The institution is currently led by Professor Edoba Bright Omoregie (SAN), who assumed office as the 11th Vice Chancellor in December 2024, succeeding Professor Lilian I. Salami.[35] Fully accredited and recognized by the National Universities Commission (NUC) of Nigeria, the university offers a wide range of courses leading to officially recognized higher education degrees. The university's population has grown significantly, with current estimates placing the student enrollment between 60,000 and 77,000.[36] The academic structure has expanded to include newer disciplines. The faculties in the university include Agriculture, Arts, Computing, Dentistry, Education, Engineering, Environmental Sciences, Law, Life Sciences, Management Sciences, Media and Communication Studies, Nursing Sciences, Pharmacy, Physical Sciences, Social Sciences, Veterinary Medicine, Vocational and Technical Education and a College of

Medical Sciences composed of the Schools of Medicine, Dentistry, Basic Medical Sciences and the Institute of Child Health.[36]

3.2 STUDY DESIGN

An analytical cross-sectional study design was adopted for this study.

3.3 STUDY DURATION

This study was conducted from December 2024 to May 2026.

3.4 STUDY POPULATION

The study was carried out among all registered undergraduate students of the University of Benin, Ugbowo Campus, Benin City, Edo State.

Selection Criteria

Inclusion Criteria:

- University of Benin students who were present at the time of data collection.
- University of Benin students who gave consent for the study.

Exclusion Criteria:

- University of Benin students who are unwilling to participate in the research.
- University of Benin students who were not available at the time of the study.

3.5 SAMPLE SIZE

The minimum sample size (n) was calculated using the Leslie Kish formula.

$$n = \frac{Z^2 pq}{d^2}$$

Where:

n = Minimum sample size

Z = Standard normal deviation set at 1.96 (at 95% confidence interval)

p = Prevalence rate of a particular characteristics of the target population

d = Desired level of precision set a 0.05 confidence interval

q = 1 – p

For this study:

p = 0.150 (15.0% based on a recent study conducted in a Nigerian federal university, which reported that less than 15% of undergraduate students utilized professional mental health support due to social labeling.[11])

q = 1 – 0.150 = 0.850

Hence:

$$n = \frac{(1.96)^2 \text{ x } (0.150) \text{ x } (0.850)}{(0.05)^2}$$

$$n = 196$$

To account for non-response, 10% non-response rate was added to the minimum sample size utilizing the formula for non-response rate.

$$n_f = \frac{n}{1 - n_r}$$

n = Minimum sample size = 196

n_r = Non-response rate = 10% = 0.10

n_f = Final minimum sample size

$$= \frac{196}{1\text{-}0.10} = \frac{196}{0.90} = 218$$

A design effect of 2 was used, to account for the multistage sampling

= 218 x 2= 436

Thus, the final minimum sample size for this study was 436.

3.6 SAMPLING TECHNIQUE

A multistage sampling technique was employed to select the respondents for this study. This method ensures that the sample is representative of the diverse undergraduate population at the University of Benin.

The process involved four stages:

Stage 1: Selection of Campus

UNIBEN has two campuses – Ugbowo and Ekenwan campuses. The Ugbowo campus of UNIBEN was selected using simple random sampling by balloting.

Stage 2: Selection of Faculties

A list of the 20 faculties in the Ugbowo campus was obtained from the Central Records Processing Unit Division; five faculties were selected using simple random sampling by balloting. The faculties selected included Medicine, Engineering, Basic Medical Sciences, Law, and Pharmacy.

Stage 3: Selection of Departments

A total of 18 departments were identified within the selected faculties. From this sampling frame, five (5) departments were selected using simple random sampling via the balloting method. The departments selected were Medicine and Surgery, Chemical Engineering, Nursing Science, Law, and Pharmacy.

Stage 4: Selection of Respondents

Within each selected department, a stratified sampling technique was applied, with each year of study constituting a stratum. The number of respondents allocated to each stratum was determined using proportional allocation.

Proportional allocation =

$$\frac{\text{Number of students in level}}{\text{Number of students in the department}} \text{ x Number of respondents in that deparment}$$

Individual respondents within each stratum were then selected using systematic random sampling. The sampling interval was calculated using this formula;

Sampling interval = $\frac{Population\ size}{Sample\ size}$

Where;

Population size = Total number of students on the class list

Sample size = Number of respondents per level

The first respondent in each stratum was selected using simple random sampling by balloting, after which every subsequent respondent was selected according to the calculated sampling interval.

3.7 DATA MANAGEMENT

3.7.1 Tools for Data Collection

A quantitative, structured, self-administered questionnaire was the primary instrument for data collection. This tool was developed by adapting globally validated standardised instruments to ensure the reliability of the clinical and technological variables being measured. Specifically, it incorporated the Patient Health Questionnaire-9 (PHQ-9), and scales from the Unified Theory of Acceptance and Use of Technology (UTAUT) model.[9 22 23] The adapted questionnaire was organized as:

SECTION A: SOCIO-DEMOGRAPHIC CHARACTERISTICS OF THE RESPONDENTS

- This section captured background information such as age, gender, faculty, level of study, religion, ethnicity and marital status.
- It also assessed socio-economic indicators by capturing the educational level and occupation of the respondent's father, mother, and/or guardian, as well as the student's average monthly allowance.

SECTION B: KNOWLEDGE OF AI CHATBOTS

- This aimed at collecting information on the respondents' knowledge of AI chatbot use in relation to mental health.
- Respondents were asked to identify specific AI tools they knew (e.g., ChatGPT, Wysa, Woebot) and their understanding of how these tools function (e.g., "Do you know these tools are automated and not human?").

SECTION C: ATTITUDE TOWARDS AI CHATBOTS

- This section aimed to ascertain the attitudes of respondents toward the use of AI chatbots for mental health support using a 3-point Likert Scale (adapted from UTAUT).
- Respondents were allowed to indicate their answers by ticking one of the opinions such as Disagree, Neutral or Agree.
- Items measured perceived trust, comfort levels (stigma reduction), and willingness to recommend AI to others.
- It also specifically assessed social and cultural determinants, including the influence of peer pressure, religious beliefs, and cultural values regarding privacy.

SECTION D: LEVEL OF AI CHATBOT USE

This section was subdivided into three specific domains to capture the depth of utilization:

- Domain 1 (Digital Access & Investment): It assessed infrastructural readiness, including smartphone ownership, type of internet access, and the specific daily, weekly, and monthly financial cost of data (in Naira).

- Domain 2 (Patterns of Use): It assessed lifetime usage, frequency of use (e.g., "Daily" vs "Rarely"), and the specific purpose of use (e.g., Mental Health Support vs. Academic Work).
- Domain 3 (Indicators of Problematic Use/Dependency): It utilized a 6-item Likert scale to assess signs of AI addiction, such as "preoccupation," "tolerance" (urge to use more), and "withdrawal" (restlessness when unable to access the AI).

SECTION E: CURRENT MENTAL HEALTH STATUS

- This section aimed to identify the current mental health status of the students using the standardized Patient Health Questionnaire-9 (PHQ-9).
- Respondents rated how often they had been bothered by nine depressive symptoms over the preceding two weeks, using a four-point scale ranging from 0 (Not at all) to 3 (Nearly every day).
- It also included three functional impairment questions to assess how difficult these problems made it for the student to perform academic work, take care of domestic duties, and interact socially.

SECTION F: FACTORS INFLUENCING THE USE OF AI CHATBOTS

- This section aimed to determine the factors influencing the use (barriers and facilitators) of AI chatbots.
- Questions assessed Facilitating Conditions (e.g., 24/7 availability, anonymity) and Barriers (e.g., high data cost, unstable electricity, fear of data leaks).
- It also assessed social context by asking about family history of mental health challenges and whether friends/peers encouraged the use of AI tool.

3.7.2 Method of Data Collection

The pre-tested structured questionnaires were self-administered at UNIBEN. The recruitment took place in the lecture theatres and faculty centers. The sample frame comprised students in the selected departments who were in the lecture hall, volunteered to be part of the study, and met the inclusion criteria. The respondents were allowed to answer the questionnaires in or around the lecture hall where they felt safe and their privacy was ensured. Informed consent was obtained from the respondents and they were assured of confidentiality.

3.7.3 Pretesting

The questionnaires were pre-tested at Benson Idahosa University, a private university located in Benin City, Edo State, to determine the reliability of data taken as it has students that have similarities with the study population. Ten percent (10%) of minimum sample size of the students were used for pretesting and observed errors were corrected before being utilized in the main study.

3.7.4 Data Analysis

The questionnaires were thoroughly checked for any errors or inconsistencies. This study utilized descriptive statistics in analyzing the data obtained. Data coding and cleaning were done, entered, and analysis was conducted with the aid of the Statistical Package for Social Sciences, IBM SPSS Statistics 25.0 software.

Univariate analysis including means, medians, and standard deviations were computed for continuous variables such as age and level of study, and results were summarised using frequency distribution tables.

Bivariate analysis using Chi square test and Fishers exact was used to test the association between socio-demographic characteristics of respondents and knowledge, attitude, level of utilisation and factors influencing use.

Multivariate analysis was used to identify the determinants of knowledge, attitude, level of utilisation and factors influencing utilization. The level of significance was set at $p < 0.050$ and the result was presented in charts, tables and prose.

3.7.5 Scoring System

Knowledge of AI Chatbots

Knowledge was assessed using a total of 13 questions. Each correct response was assigned a score of 1, while each incorrect response or "I don't know" was assigned a score of 0. Scores were summed and converted to a percentage, then classified as follows:

- A score 0% - 49.9% was regarded as Poor Knowledge.
- A score 50% - 100% was regarded as Good Knowledge.

Attitude Towards AI Chatbots

Attitude was assessed using a total of 14 questions on a 3-point Likert scale with response options of Agree, Neutral, and Disagree. The appropriate or positive response was assigned a score of 3, the neutral response a score of 2, and the inappropriate or negative response a score of 1. Negative items were reverse-coded prior to scoring. The mean score across all attitude items was then calculated and classified as follows:

- Mean Score < 3.0 was regarded as Negative Attitude.
- Mean Score ≥ 3.0 was regarded as Positive Attitude.

Uptake and Level of AI Chatbot Use

The utilization of AI chatbots was evaluated across three analytical metrics:

Prevalence/Uptake (Based on Q49):

This established the baseline adoption rate. Respondents were categorized as:

- Users: Those who selected "Yes" to having ever used an AI chatbot.

- Non-Users: Those who selected "No" (and subsequently skipped to Section E).

Level of Utilization (Based on Q50):

Among active users, a composite utilization score was derived from frequency of use and average daily hours spent on AI chatbots. Respondents were dichotomized as:

- High-Frequency Users: Respondents who indicated using AI chatbots "Often" or "Very Often".
- Moderate/Low-Frequency Users: Respondents who indicated using them "Sometimes," "Rarely", or "Very Rarely".

Daily hours of use were also described descriptively as a continuous variable.

Problematic Use/Dependency Score (Based on Domain 3, Q53–Q58):

Psychological dependency was also assessed using a 6-item Likert scale measuring preoccupation, tolerance, escape, persistence, withdrawal, and conflict. Responses were scored from 1 (Very Rarely) to 5 (Very Often). The 6 items were summed to create a Composite Dependency Score ranging from 6 to 30:

- Score 6 – 12 (Normal/Controlled Use): Indicates minimal to no dependency; use is functional and does not disrupt daily life.
- Score 13 – 20 (At-Risk Use): Indicates moderate engagement with emerging signs of compulsion or using AI as a primary coping mechanism for real-life stress.
- Score 21 – 30 (Problematic Dependency): Indicates a high level of dependency, where AI use negatively impacts academic studies, relationships, and emotional stability.

For bivariate and multivariate analysis, scores were dichotomized into two categories:

- Low Dependency: Score 6–20 (Normal and At-Risk combined)
- High Dependency: Score 21–30 (Problematic Dependency)

Current Mental Health Status

The PHQ-9 items were scored from 0 (Not at all) to 3 (Nearly every day). The total score (0-27) was interpreted as follows:

- 0 – 4: Minimal Depression
- 5 – 9: Mild Depression
- 10 – 14: Moderate Depression
- 15 – 19: Moderately Severe Depression
- 20 – 27: Severe Depression

For the purposes of bivariate and multivariate analysis, respondents were dichotomized into two categories using a validated cut-off score:

- Not Depressed: PHQ-9 score of 0–4
- Depressed: PHQ-9 score of ≥ 5

Factors Influencing Use

Factors influencing AI chatbot use were analyzed using inferential statistics. Bivariate associations between independent variables – including sociodemographic characteristics, peer influence, privacy concerns, infrastructural barriers, and facilitating conditions – and the dependent variables of uptake, utilization, and dependency were assessed using the chi-square test or Fisher's exact test where appropriate. Variables attaining statistical significance at the bivariate level were entered into a backward stepwise binary logistic regression model to identify independent predictors. A p-value of < 0.050 was considered statistically significant throughout.

3.8 DATA PRESENTATION

Findings from the study were presented using frequency distribution tables, contingency tables, charts, and narrative descriptions. These methods facilitated the clear presentation of response distributions, relationships between variables, and key trends observed in the data.

3.9 ETHICAL CONSIDERATION

Institutional permission and ethical clearance were obtained from the Health Research Ethics Committee of the University of Benin Teaching Hospital (UBTH). **Ethical Clearance Number: ADM/E 22/A/VOL. VII/14865491272118**. Informed consent was also obtained from respondents before administering the questionnaires. Respondents were informed that they have the right to withdraw from the study at any time, and that doing so poses no loss or harm. Participants' confidentiality and anonymity were ensured, and no identifying information was collected. Data obtained were used strictly for research purposes.

Participation in this study offered potential benefits to respondents and the broader student population. Completing the questionnaire provided respondents with an opportunity to reflect on their own mental health status and patterns of AI chatbot engagement, which may itself promote self-awareness regarding psychological well-being. Furthermore, the findings of this study are intended to inform evidence-based recommendations for university management, policymakers, and digital health developers, with the ultimate aim of improving the availability, safety, and accessibility of mental health support services for undergraduate students at the University of Benin and similar institutions.

3.10 STUDY LIMITATION

This study was subject to several methodological limitations that should be considered when interpreting its findings.

First, the cross-sectional study design precluded the establishment of causal relationships between variables. This is particularly relevant to the observed associations between AI chatbot utilization, dependency, and depressive symptoms, where the directionality of effect – whether AI use contributes to depression, whether depressed students are more likely to engage intensively with AI tools, or whether both reflect shared underlying vulnerabilities – cannot be determined from this data alone. Longitudinal studies are needed to clarify these relationships.

Second, data were obtained exclusively through self-administered questionnaires, introducing the potential for recall bias in the reporting of AI usage frequency and duration, and social desirability bias in the disclosure of depressive symptoms and dependency-related behaviours. Respondents may have under-reported or over-reported behaviours they perceived as stigmatized or socially undesirable.

Third, mental health status was assessed using the Patient Health Questionnaire-9 (PHQ-9), a validated screening instrument rather than a diagnostic tool. A positive screen indicates probable depression but does not constitute a clinical diagnosis. The prevalence figures reported in this study therefore represent screening-level estimates and may not correspond precisely to the true clinical prevalence of depressive disorder within the population.

Finally, the study relied on respondents' self-reported patterns of AI chatbot use, including frequency, duration, and purpose of engagement. As AI chatbot use may carry social desirability implications in both directions – either as a marker of technological sophistication or as an indicator of emotional vulnerability – reported usage patterns may not fully reflect actual behaviour.

CHAPTER FOUR

RESULTS

A total of 436 questionnaires were administered in this study and were all completely filled, giving a response rate of 100%. The results are presented in the following sections in line with the specific objectives.

SECTION A: Sociodemographic characteristics of the respondents

SECTION B: Knowledge of AI mental health chatbots among respondents

SECTION C: Attitudes of respondents toward AI mental health chatbots

SECTION D: Use of AI chatbots among respondents

SECTION E: Mental health status of respondents

SECTION F: Factors influencing the use of AI chatbots among respondents

SECTION A

Sociodemographic characteristics of the respondents

Table 1: Sociodemographic characteristics of respondents (n = 436)

Variable	Frequency (n = 436)	Percent
Age (years)		
< 18	21	4.8
18 - 24	347	79.6
25 - 30	59	13.5
> 30	9	2.1
Gender		
Male	257	58.9
Female	179	41.1
Religion		
Christianity	290	66.5
Islam	138	31.7
Others[a]	8	1.8
Faculty		
Medical[b]	274	62.8
Non-Medical[c]	162	37.2
Department		
Medical[d]	274	62.8
Non-Medical[e]	162	37.2
Ethnicity		
Edo indigenes	229	52.5
Non-Edo indigenes[f]	191	43.8
Marital Status		
Never Married[g]	412	94.5
Ever Married	24	5.5
Level of Study		
100 Level	33	7.6
200 Level	111	25.5
300 Level	114	26.1
400 Level	82	18.8
500 Level	60	13.8
600 Level	36	8.3
Father's Level of Education		
Tertiary	336	77.1
Secondary	80	18.3
Primary	8	1.8
None	12	2.8
Mother's Level of Education		
Tertiary	293	67.2
Secondary	104	23.9
Primary	27	6.2
None	12	2.8
Current Living Arrangement		
On-campus	207	47.5
Off-campus	229	52.5
Socioeconomic Class		
Lower Class	43	9.9
Middle Class	287	65.8
Upper Class	106	24.3

[a]African Traditional Religion, Atheist/Agnostic. [b]Medicine and Surgery, Medicine, Basic Medical Sciences (BMS), Nursing Sciences, Nursing, Pharmacy, Optometry, Dentistry, Health Sciences. [c]Engineering, Law, Computing, Computer Science, Education, Agriculture, Arts, Management

Sciences, Physical Sciences, Environmental Sciences, Life Sciences, Social Sciences.. [d]Medicine and Surgery, Medicine, Anatomy, Human Anatomy, Physiology, Medical Biochemistry, Nursing, Nursing Sciences, Pharmacy, Dentistry, Optometry, Medical Laboratory Science (MLS), Radiography, Physiotherapy. [e]Chemical Engineering, Civil Engineering, Electrical/Electronics Engineering, Mechanical Engineering, Petroleum Engineering, Mechatronics, Software Engineering, Material and Metallurgical Engineering, Structural Engineering, Geomatics, Law, Accounting, Economics, Banking and Finance, Actuarial Science, Business Administration, Computer Science, Mathematics, Chemistry, Microbiology, Geology, Fisheries and Aquaculture, Animal Science, Architecture, Estate Management, Geography and Disaster Risk Management, Glass and Silicate Technology, History, Linguistics, Marine, Mass Communication, Biology Education, Science Laboratory Technology (SLT). [f] Yoruba, Igbo, Hausa, Esan, Etsako, Urhobo, Ebira, Ibibio, Ijaw, Igarra, Isoko, Itsekiri, Akoko-edo, Egbira, Igala, Imiegba, Okpe, Kogi, Ogoni (Rivers State). [g]Single, cohabiting.

A total of 436 respondents participated in the study. In relation to age, the respondents studied had a mean age of 21.84 ± 3.97 years, with ages ranging from 16 to 50 years. In relation to gender, male respondents comprised over half (58.9%) of the study population, with female respondents being the least at 41.1%. In relation to academic affiliation, respondents enrolled in medical faculties and departments comprised nearly two-thirds (62.8%) of the total respondents, with the least being those from non-medical disciplines (37.2%). In relation to ethnicity, Edo indigenes constituted the largest demographic comprising over half (52.5%) of the total respondents, with the least being Non-Edo indigenes (43.8%).

In relation to marital status, never-married respondents comprised the overwhelming bulk (94.5%) of the total respondents, with the least being those who had ever been married (5.5%). In relation to the level of study, 300 Level students comprised the largest group at over a quarter (26.1%) of the total respondents, with the least being 100 Level students (7.6%).

In relation to parental educational background, respondents whose fathers and mothers attained tertiary-level education comprised the clear majority at 77.1% and 67.2% respectively, with the least being those with secondary-level education at 18.3% and 23.9% respectively. In relation to living arrangements, respondents residing on-campus comprised nearly half (47.5%) of the total respondents, while those residing off-campus comprised the majority (52.5%). Finally, in relation to socioeconomic class, respondents from a Middle-Class background comprised nearly two-thirds (65.8%) of the total respondents, with the least being the Lower-Class category (9.9%).

SECTION B

Knowledge of AI mental health chatbots among respondents

Table 2: Awareness and sources of information about AI chatbots (n = 436)

Variable	Frequency (n = 436)	Percent
Have you ever heard of the term "AI Chatbot"?		
Yes	420	96.3
No	16	3.7
Source of information (n = 420) *		
Social media (Twitter, TikTok, etc.)	287	65.8
School/University Lectures	253	58.0
Friends/Peers	203	46.6
YouTube Videos	126	28.9
Television/Radio	46	10.6
Other[a]	9	2.1

*Multiple response question (percentages may exceed 100%) [a]Web2 and Web3, Everywhere, Found out by myself, Google, Personal discovery, ChatGPT & Grok, Copilot.

As shown in Table 2, in relation to awareness of the term "AI Chatbot", respondents who had heard of the term comprised the overwhelming majority (96.3%) of the total respondents, with the least being those who had not (3.7%). In relation to the source of information about AI chatbots, respondents who learned through social media platforms constituted the largest group, comprising nearly two-thirds (65.8%) of the total respondents, with the least being those who learned through television or radio (10.6%).

In relation to awareness of the mental health-specific application of AI chatbots, respondents who were aware that AI chatbots can be used to support mental health comprised over three-quarters (76.4%) of the total respondents, with the least being those who were not aware (23.6%). Finally, in relation to the nature of AI, respondents who knew that AI chatbots are automated programs and not real human beings comprised the overwhelming bulk (95.2%) of the total respondents, with the least being those who did not (4.8%).

Table 3: Knowledge responses of AI chatbots among university students (n = 420)

Variables	Frequency (n = 420)	Percent (%)
Awareness of AI Tools*		
ChatGPT	394	93.8
Gemini	340	81.0
Meta AI (WhatsApp/Instagram)	306	72.9
Snapchat MyAI	135	32.1
Woebot (Mental Health Specific)	10	2.4
Wysa (Mental Health Specific)	8	1.9
Conceptual Definition of AI Mental Health Chatbot		
An automated software program that uses algorithms to mimic human conversation	325	77.4
A real human doctor chatting with you online	50	11.9
I don't know	23	5.5
A video call with a therapist	17	4.0
Awareness of Mental Health Applications of AI Chatbots		
Yes	323	76.9
No	92	21.9
Identification of the Capabilities of AI chatbots*		
Coping Tips and Mindfulness Exercises	345	82.1
Tracking Mood and Emotional Patterns	219	52.1
Anonymous Platform to Vent Feelings	200	47.6
Prescribe Psychiatric Medications	375	89.3
Understanding of AI Chatbots as computer programs		
Yes	401	95.5
No	14	3.3

*Multiple response questions. $\alpha = 0.771$

In relation to specific AI tools heard of, respondents who recognized ChatGPT comprised the overwhelming bulk (93.8%) of the total respondents, followed by those who recognized Gemini (81.0%) and Meta AI (72.9%), while the least were respondents who selected "None of the Above"

(0.5%). Awareness of mental-health-specific chatbots was notably poor, as only a very small minority recognized Woebot (2.4%) and Wysa (1.9%).

In relation to the conceptual definition of an AI mental health chatbot, respondents who correctly described it as an automated software program that mimics human conversation comprised over three-quarters (77.4%) of the total respondents, while the least proportion described it incorrectly as a video call with a therapist (4.0%). A smaller proportion either perceived it as a real human doctor chatting online (11.9%) or indicated they did not know its meaning (5.5%).

In relation to awareness of mental health applications of AI chatbots, respondents who confirmed awareness that AI chatbots can support mental health comprised over three-quarters (76.9%) of the total respondents, while about one-fifth (21.9%) indicated they were not aware.

In relation to perceived capabilities of AI chatbots, respondents who identified provision of coping tips and mindfulness exercises comprised the vast majority (82.1%) of the total respondents, followed by those who recognized mood and emotional pattern tracking (52.1%), while the least acknowledged capability was provision of an anonymous platform to vent feelings (47.6%). However, respondents who incorrectly indicated that AI chatbots can prescribe psychiatric medications comprised the overwhelming bulk (89.3%), suggesting a significant misconception regarding the functional limits of these technologies.

In relation to understanding the fundamental nature of AI chatbots, respondents who correctly affirmed that AI chatbots are automated programs and not real humans comprised almost all (95.5%) of the respondents, while only a small minority (3.3%) indicated otherwise.

Finally, in relation to the overall composite knowledge score, respondents classified as having good knowledge about AI chatbots comprised the vast majority (90.2%) of the total respondents, while the least were those classified as having poor knowledge (9.8%).

Table 4: Correctness of Knowledge Responses on AI Mental Health Chatbots (n = 420)

Variables	Responses	
	Correct Freq (%)	**Incorrect Freq (%)**
Knowledge of AI Tools*		
ChatGPT	398 (94.8%)	22 (5.2%)
Gemini	343 (81.7%)	77 (18.3%)
Meta AI (WhatsApp/Instagram)	308 (73.3%)	112 (26.7%)
Snapchat MyAI	135 (32.1%)	285 (67.9%)
Woebot (mental health-specific)	11 (2.6%)	409 (97.4%)
Wysa (mental health-specific)	8 (1.9%)	412 (98.1%)
Conceptual Definition of AI Mental Health Chatbot		
An automated software program that uses algorithms to mimic human conversation.	328 (78.1%)	92 (21.9%)
Awareness of Mental Health Applications of AI Chatbots		
Aware that AI Chatbots can be used specifically to support mental health (therapy/counseling)	324 (77.1%)	96 (22.9%)
Identification of the Capabilities of AI chatbots*		
Providing coping tips and mindfulness exercises	348 (82.9%)	72 (17.1%)
Tracking mood and emotional patterns	223 (53.1%)	197 (46.9%)
Providing an anonymous platform to vent feelings	202 (48.1%)	218 (51.9%)
Can prescribe psychiatric medications	380 (90.5%)	40 (9.5%)
Understanding of AI Chatbots		
Understand that these AI chatbots are automated computer programs and not real humans	401 (95.5%)	19 (4.5%)

*Multiple response questions

In relation to awareness of specific AI tools, respondents who correctly identified ChatGPT comprised the overwhelming bulk (94.8%) of the total respondents, followed by those who correctly identified Gemini (81.7%) and Meta AI (73.3%), while recognition was markedly lower for Snapchat MyAI (32.1%). Awareness of mental health-specific AI tools was particularly poor, as only a very small minority correctly identified Woebot (2.6%) and Wysa (1.9%), indicating limited familiarity with specialized mental health chatbots.

In relation to the conceptual definition of an AI mental health chatbot, respondents who correctly identified it as an automated software program that mimics human conversation comprised over three-quarters (78.1%) of the total respondents, while about one-fifth (21.9%) selected incorrect definitions.

In relation to awareness that AI chatbots can be used specifically to support mental health, respondents who answered correctly comprised over three-quarters (77.1%) of the total respondents, whereas less than one-quarter (22.9%) demonstrated incorrect knowledge.

In relation to knowledge of the capabilities of AI chatbots in mental health support, respondents who correctly recognized that AI chatbots cannot prescribe psychiatric medications comprised the vast majority (90.5%) of the total respondents, representing the highest correct response among capability-related items. This was followed by respondents who correctly identified provision of coping tips and mindfulness exercises (82.9%). Slightly above half (53.1%) correctly recognized mood and emotional pattern tracking as a chatbot function, while the least proportion (48.1%) correctly identified provision of an anonymous platform to vent feelings, suggesting comparatively lower awareness of this supportive function.

In relation to understanding the fundamental nature of AI chatbots, respondents who correctly affirmed that AI chatbots are automated programs rather than real humans comprised almost all (95.5%) of the respondents, representing the highest proportion of correct responses across all knowledge items, while only a small minority demonstrated incorrect understanding.

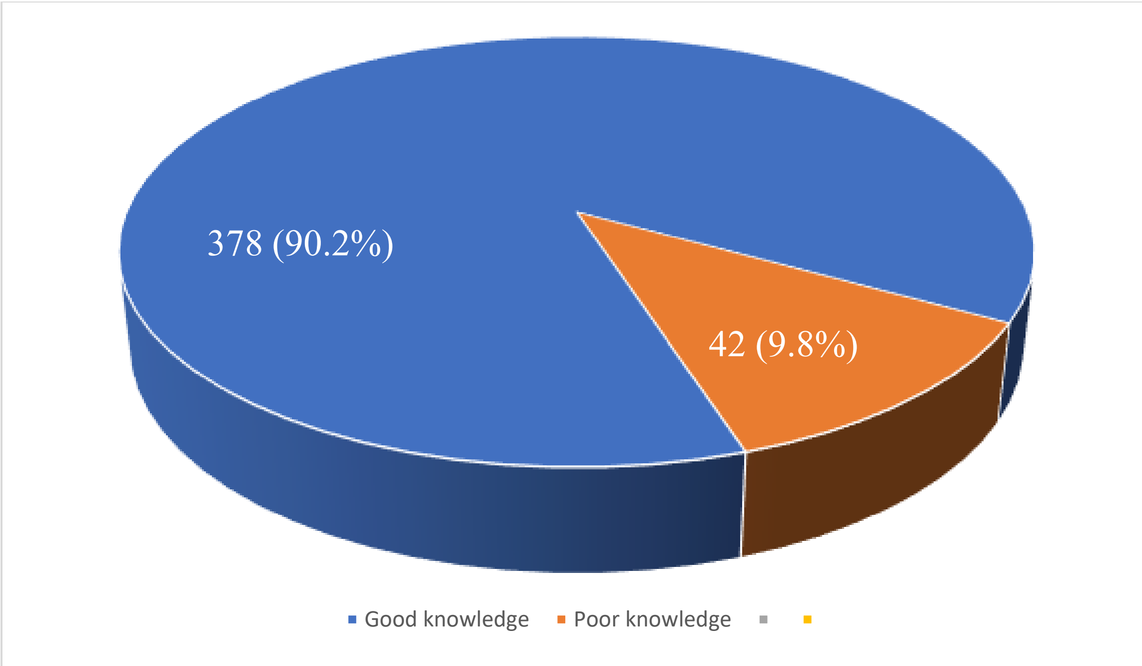

Figure 1: Knowledge level of AI chatbots among respondents

Most of the respondents 378 (90.2%) had good knowledge of AI chatbots, while some of them 42 (9.8%) had poor knowledge.

Table 5: Socio-demographic characteristics and knowledge of AI chatbots (n = 420)

Variables	Knowledge of AI Chatbots		Test statistic	p-value
	Poor Freq (%)	Good Freq (%)		
Age (years)				
< 18	4 (19.0%)	17 (81.0%)	2.499	0.645
18 - 24	116 (34.9%)	216 (65.1%)		
25 - 30	21 (35.6%)	38 (64.4%)		
> 30	3 (37.5%)	5 (62.5%)		
Gender				
Male	87 (35.8%)	156 (64.2%)	0.589	0.443
Female	57 (32.2%)	120 (67.8%)		
Religion				
Christianity	98 (34.8%)	184 (65.2%)	0.155*	0.973
Islam	44 (33.6%)	87 (66.4%)		
Others	2 (28.6%)	5 (71.4%)		
Faculty				
Non-Medical	58 (37.2%)	98 (62.8%)	0.922	0.337
Medical	86 (32.6%)	178 (67.4%)		
Department				
Non-Medical	57 (36.3%)	100 (63.7%)	0.454	0.500
Medical	87 (33.1%)	176 (66.9%)		
Marital Status				
Never Married	134 (33.8%)	262 (66.2%)	0.615	0.433
Ever Married	10 (41.7%)	14 (58.3%)		
Ethnicity				
Edo indigenes	88 (38.4%)	141 (61.6%)	3.441	**0.064**
Non-Edo indigenes	56 (29.3%)	135 (70.7%)		
Level of study				
100L	14 (46.7%)	16 (53.3%)	11.235	**0.047**
200L	35 (33.0%)	71 (67.0%)		
300L	45 (41.3%)	64 (58.7%)		
400L	24 (30.4%)	55 (69.6%)		
500L	21 (34.4%)	40 (65.6%)		
600L	5 (14.3%)	30 (85.7%)		
Socioeconomic class				
Lower	14 (34.1%)	27 (65.9%)	0.008	0.996
Middle	95 (34.2%)	183 (65.8%)		
Upper	35 (34.7%)	66 (65.3%)		
Current living arrangement				
On campus	78 (38.6%)	124 (61.4%)	3.236	0.072
Off campus	66 (30.3%)	152 (69.7%)		

*Fisher-Freeman-Halton exact test

In relation to ethnicity, Non-Edo indigenes comprised a higher proportion of respondents with good knowledge (70.7%) compared with Edo indigenes (61.6%). However, this observed difference was not statistically significant ($\chi^2 = 3.441$, $p = 0.064$), indicating no significant association between ethnicity and knowledge of AI chatbots.

In relation to level of study, respondents in 600 level comprised the highest proportion with good knowledge (85.7%), followed by those in 400 level (69.6%), 200 level (67.0%), 500 level (65.6%), and 300 level (58.7%), while 100 level respondents comprised the least proportion with good knowledge (53.3%). This association was statistically significant ($\chi^2 = 11.235$, $p = 0.047$), indicating that level of study was significantly associated with respondents' knowledge of AI chatbots.

All other socio-demographic variables examined, including age, gender, religion, faculty, department, marital status, social class, and current living arrangement, were not statistically significantly associated with knowledge of AI chatbots ($p > 0.050$).

Table 6: Predictors of knowledge of AI chatbots

Predictors	β	Odds ratio	95% CI for OR (Lower)	95% CI for OR (Upper)	p-value
Age					
< 18 *		1			
18 - 24	0.841	0.431	0.122	1.522	0.191
25 - 30	1.229	0.293	0.079	1.081	**0.021**
> 30	1.622	0.198	0.050	0.787	**0.007**
Ethnicity					
Edo indigenes *		1			
Non-Edo indigenes	0.409	1.505	0.999	2.267	0.051
Level of study					
100L *		1			
200L	0.840	2.317	0.913	5.882	0.077
300L	0.544	1.723	0.667	4.451	0.261
400L	1.251	3.495	1.232	9.915	**0.019**
500L	1.012	2.752	0.927	8.172	0.068
600L	2.049	7.758	1.923	31.300	**0.004**
Gender					
Male *	—	1	—	—	—
Female	-0.003	0.997	0.620	1.602	0.990
Religion					
Christianity*	—	1	—	—	—
Islam	0.069	1.071	0.607	1.891	0.813
Others	0.226	1.254	0.211	7.451	0.804
Marital Status					
Never Married *	—	1	—	—	—
Ever Married	-0.767	0.464	0.172	1.255	0.130

*Reference variable

A backward stepwise (conditional) logistic regression was performed to identify the sociodemographic predictors of having good knowledge of AI chatbots. The initial full model included age, gender, religion, faculty, department, marital status, ethnicity, level of study, monthly income, socioeconomic class, and current living arrangement. After six elimination steps, the final parsimonious model retained age, ethnicity, level of study, and monthly income as reliable significant predictors (Table 6).

Age demonstrated a significant negative association with knowledge levels. Compared to the youngest students (< 18 years), older age groups had lower odds of possessing good knowledge of AI chatbots. Specifically, students aged 25–30 years (OR = 0.198, 95% CI: 0.050–0.787, p = 0.021) and those aged above 30 years (OR = 0.119, 95% CI: 0.025–0.562, p = 0.007) were markedly less likely to have good knowledge.

Ethnicity was not a statistically significant predictor of good knowledge. Non-Edo indigenes had slightly higher odds of demonstrating good knowledge compared to Edo indigenes (OR = 1.505, 95% CI: 0.999–2.267, p = 0.051), though this did not reach statistical significance.

Furthermore, higher Level of Study was significantly associated with better knowledge. Students in their fourth year (400L) had 3.49 times higher odds of good knowledge (95% CI: 1.232–9.915, p = 0.019), and those in their sixth year (600L) had 7.75 times higher odds (95% CI: 1.923–31.300, p = 0.004) compared to first-year (100L) students.

Several variables from the initial model were excluded from the final results. Gender, religion, marital status, socioeconomic class, and current living arrangement were found to be non-significant and were sequentially removed from the model during the stepwise process (p > 0.05). Additionally, faculty and department exhibited multicollinearity/quasi-complete separation during the analysis, leading to non-convergence, inflated standard errors, and extreme odds ratios. Due to this, they could not be reliably interpreted individually and were consequently excluded from the final table.

SECTION C

Attitudes of respondents toward AI mental health chatbots

Table 7: Attitudes of respondents towards the use of AI chatbots

Variables	Attitudinal responses		
	A Freq (%)	**N Freq= (%)**	**D Freq (%)**
AI chatbots can effectively influence a student's decision to seek help for mental health	210 (50.0%)	159 (37.9%)	51 (12.1%)
Content provided by AI chatbots for mental health support should be regulated by the University	158 (37.6%)	203 (48.3%)	59 (14.0%)
Developers and tech companies should be cautious about how AI interacts with students in distress	248 (59.0%)	121 (28.8%)	51 (12.1%)
Relying on AI chatbots for emotional support normalises isolation from real people	56 (13.3%)	176 (41.9%)	188 (44.8%)
AI chatbots can be used effectively to educate students about mental health dangers	266 (63.3%)	127 (30.2%)	27 (6.4%)
I would report an AI chatbot if it gave harmful or dangerous advice	238 (56.7%)	133 (31.7%)	49 (11.7%)
University policies should promote the use of safe AI tools for student support	251 (59.8%)	128 (30.5%)	41 (9.8%)
I support regulations that limit the types of advice AI can give (e.g., no medical diagnosis)	240 (57.1%)	144 (34.3%)	36 (8.6%)
Peer pressure plays a major role in whether I would use an AI chatbot	127 (30.2%)	166 (39.5%)	127 (30.2%)
Seeing friends post about using AI tools would influence my perception of them	137 (32.6%)	166 (39.5%)	117 (27.9%)
My religious beliefs discourage me from seeking emotional help from machines	219 (52.1%)	134 (31.9%)	67 (16.0%)
Religious leaders should speak more about the role of technology in mental well-being	143 (34.0%)	189 (45.0%)	88 (21.0%)
My cultural background influences my views about sharing secrets with a robot	71 (16.9%)	168 (40.0%)	181 (43.1%)
Cultural values regarding privacy make AI chatbots a better option than public counselling	100 (23.8%)	205 (48.8%)	115 (27.4%)

Key: A = Agree, N = Neutral, D = Disagree. α = 0.709

In relation to attitudes toward the potential of AI chatbots to influence help-seeking for mental health concerns, respondents who agreed that AI chatbots can effectively influence a student's decision to seek help comprised half (50.0%) of the total respondents, while the least proportion disagreed (12.1%), suggesting a generally favorable disposition toward their supportive role.

In relation to regulation and institutional oversight of AI chatbots, respondents who were neutral on whether mental health content provided by AI chatbots should be regulated by the university comprised the largest proportion (48.3%), followed by those who agreed (37.6%), while the least disagreed (14.0%). Similarly, respondents who agreed that developers and technology companies should exercise caution in how AI interacts with students in distress comprised the majority (59.0%), while only a small minority disagreed (12.1%). Furthermore, respondents who supported university policies promoting safe AI tools for student support comprised the majority (59.8%), while the least disagreed (9.8%). Likewise, respondents who agreed that regulations should limit the type of advice AI chatbots can provide comprised over half (57.1%), with only a minority disagreeing (8.6%). These findings reflect generally positive attitudes toward institutional and ethical regulation of AI mental health tools.

In relation to perceived usefulness of AI chatbots in mental health education, respondents who agreed that AI chatbots can effectively educate students about mental health dangers comprised nearly two-thirds (63.3%) of respondents, representing the highest level of agreement across all attitude items, while the least proportion disagreed (6.4%). Similarly, respondents who indicated they would report an AI chatbot if it gave harmful or dangerous advice comprised over half (56.7%), suggesting considerable awareness of accountability and safety concerns.

In relation to perceptions of the social and psychological implications of AI chatbot use, respondents who disagreed that relying on AI chatbots for emotional support normalizes isolation from real people comprised the largest proportion (44.8%), while only 13.3% agreed, indicating that most respondents did not perceive chatbot use as inherently socially isolating.

In relation to social influences on AI chatbot use, respondents were largely neutral regarding peer pressure as a determinant of use (39.5%), while equal proportions agreed and disagreed (30.2% respectively), suggesting no clear consensus regarding peer influence. Similarly, neutrality comprised the largest proportion (39.5%) regarding whether seeing friends post about AI tools would shape respondents' perceptions, while agreement (32.6%) and disagreement (27.9%) were comparatively lower.

In relation to religious and cultural influences, respondents who agreed that religious beliefs may discourage seeking emotional help from machines comprised over half (52.1%), while the least disagreed (16.0%), suggesting religion may constitute a notable attitudinal consideration. However, respondents were predominantly neutral (45.0%) regarding whether religious leaders should speak more on technology and mental well-being. With respect to cultural influences, respondents who disagreed that cultural background affects willingness to share secrets with a robot comprised the largest proportion (43.1%), while only a minority agreed (16.9%). Similarly, neutrality comprised the largest proportion (48.8%) regarding whether cultural values around privacy make AI chatbots preferable to public counselling, suggesting uncertainty in respondents' attitudes on this issue.

Overall, the pattern of responses suggests generally favorable attitudes toward the supportive, educational, and regulated use of AI chatbots for mental health, although neutrality was prominent across several socio-cultural items, indicating areas of attitudinal uncertainty.

Table 8: Appropriateness of Responses to Attitudinal Questions on AI Chatbots among Respondents (n = 420)

Variables	Attitudinal responses	
	Appropriate Freq (%)	**Inappropriate Freq (%)**
AI chatbots can effectively influence a student's decision to seek help for mental health	290 (69.0%)	130 (31.0%)
Content provided by AI chatbots for mental health support should be regulated by the University	260 (61.9%)	160 (38.1%)
Developers and tech companies should be cautious about how AI interacts with students in distress	309 (73.6%)	111 (26.4%)
Relying on AI chatbots for emotional support normalises isolation from real people	276 (65.7%)	144 (34.3%)
AI chatbots can be used effectively to educate students about mental health dangers	330 (78.6%)	90 (21.4%)
I would report an AI chatbot if it gave harmful or dangerous advice	305 (72.6%)	115 (27.4%)
University policies should promote the use of safe AI tools for student support	315 (75.0%)	105 (25.0%)
I support regulations that limit the types of advice AI can give (e.g., no medical diagnosis)	312 (74.3%)	108 (25.7%)
Peer pressure plays a major role in whether I would use an AI chatbot	210 (50.0%)	210 (50.0%)
Seeing friends post about using AI tools would influence my perception of them	200 (47.6%)	220 (52.4%)
My religious beliefs discourage me from seeking emotional help from machines	134 (31.9%)	286 (68.1%)
Religious leaders should speak more about the role of technology in mental well-being	238 (56.7%)	182 (43.3%)
My cultural background influences my views about sharing secrets with a robot	265 (63.1%)	155 (36.9%)
Cultural values regarding privacy make AI chatbots a better option than public counselling	203 (48.3%)	217 (51.7%)

$\alpha = 0.709$

In relation to the appropriateness of respondents' attitudes toward the supportive and educational roles of AI chatbots, respondents who provided appropriate responses to the use of AI chatbots in educating students about mental health dangers comprised the vast majority (78.6%) of the total respondents, representing the highest proportion of appropriate responses across all attitude items. This was followed by respondents who appropriately supported university policy promotion of safe AI tools for student support (75.0%), regulations limiting the types of advice AI chatbots can provide (74.3%), and caution by developers in AI-student interactions (73.6%). Similarly, respondents who appropriately indicated willingness to report an AI chatbot giving harmful or dangerous advice comprised nearly three-quarters (72.6%), reflecting generally favorable and safety-conscious attitudes toward AI mental health support.

In relation to attitudes regarding help-seeking and social implications of chatbot use, respondents who provided appropriate responses on the role of AI chatbots in influencing students' decisions to seek mental health support comprised over two-thirds (69.0%) of respondents. Likewise, respondents who appropriately disagreed with the notion that reliance on AI chatbots normalizes social isolation comprised the majority (65.7%), suggesting that most respondents did not perceive chatbot use as inherently socially harmful.

In relation to institutional regulation of AI mental health tools, respondents who appropriately endorsed university regulation of AI-generated mental health content comprised over three-fifths (61.9%) of respondents, indicating moderate support for institutional oversight.

In relation to social influences on attitudes toward AI chatbot use, responses were mixed. Respondents who provided appropriate responses regarding peer pressure as a determinant of AI chatbot use comprised exactly half (50.0%) of the total respondents, equal to those with inappropriate responses, suggesting no clear attitudinal direction on peer influence. Furthermore, respondents with inappropriate responses regarding social media influence on perceptions of AI tool users slightly exceeded those with appropriate responses (52.4% versus 47.6%), indicating that social influence remained a notable factor shaping attitudes.

In relation to religious and cultural influences, respondents who provided appropriate responses to the reversed item on cultural background affecting willingness to share secrets with a robot comprised over three-fifths (63.1%), while respondents who appropriately supported greater involvement of religious leaders in discussions on technology and mental well-being comprised over half (56.7%). However, fewer than half (48.3%) provided appropriate responses regarding cultural privacy values making AI chatbots preferable to public counselling.

Notably, the lowest proportion of appropriate responses across all attitude items was recorded for the reversed item on religious beliefs discouraging the use of AI for emotional support, where only 31.9% provided appropriate responses. This suggests that religious beliefs constituted the most pronounced barrier to appropriate attitudes toward AI mental health chatbot use.

Overall, the pattern of responses indicates generally appropriate attitudes toward the educational, supportive, and regulated use of AI chatbots, although socio-cultural and religious factors appeared to remain important constraints.

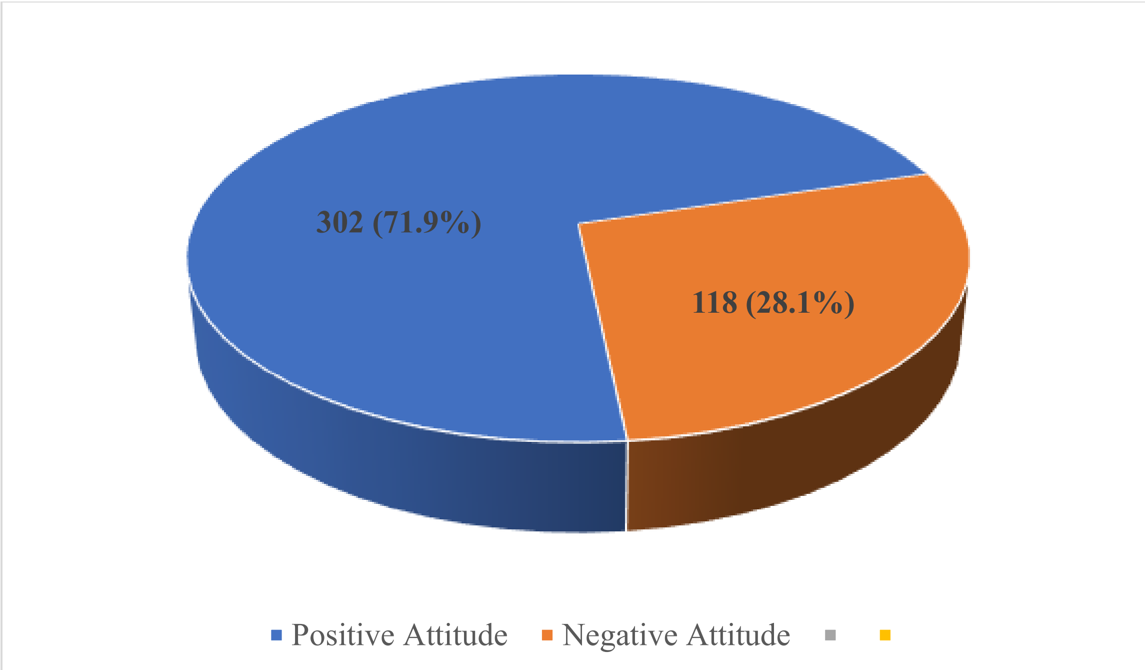

Figure 2: Level of Attitude towards AI chatbots

More than two-thirds, 302 (71.9%) of the respondents had a positive attitude towards AI mental health chatbot use, while less than one-third, 118 (28.1%), had a negative attitude.

Table 9: Factors associated with attitudes towards AI chatbots

Variables	Attitudinal responses		Test statistic	p-value
	Positive Freq (%)	Negative Freq (%)		
Age (years)				
< 18	20 (95.2%)	1 (4.8%)	7.310	0.120
18 - 24	230 (69.3%)	102 (30.7%)		
25 - 30	42 (71.2%)	17 (28.8%)		
> 30	6 (75.0%)	2 (25.0%)		
Gender				
Male	165 (67.9%)	78 (32.1%)	2.605	0.127
Female	133 (75.1%)	44 (24.9%)		
Religion				
Christianity	188 (66.7%)	94 (33.3%)	8.152*	**0.013**
Islam	105 (80.2%)	26 (19.8%)		
Others	5 (71.4%)	2 (28.6%)		
Faculty				
Medical	184 (69.7%)	80 (30.3%)	0.544	0.461
Non-Medical	114 (73.1%)	42 (26.9%)		
Department				
Medical	183 (69.6%)	80 (30.4%)	0.641	0.423
Non-Medical	115 (73.2%)	42 (26.8%)		
Marital Status				
Never Married	286 (72.2%)	110 (27.8%)	5.422	**0.020**
Ever Married	12 (50.0%)	12 (50.0%)		
Ethnicity				
Edo indigenes	164 (71.6%)	65 (28.4%)	0.048	0.826
Non-Edo indigenes	134 (70.2%)	57 (29.8%)		
Level of study				
100L	23 (76.7%)	7 (23.3%)	11.735	**0.039**
200L	69 (65.1%)	37 (34.9%)		
300L	70 (64.2%)	39 (35.8%)		
400L	57 (72.2%)	22 (27.8%)		
500L	48 (78.7%)	13 (21.3%)		
600L	31 (88.6%)	4 (11.4%)		
Socioeconomic class				
Lower	31 (75.6%)	10 (24.4%)	1.608	0.448
Middle	200 (71.9%)	78 (28.1%)		
Upper	67 (66.3%)	34 (33.7%)		
Living arrangement				
On campus	138 (68.3%)	64 (31.7%)	1.312	0.252
Off campus	160 (73.4%)	58 (26.6%)		
Level of Knowledge				
Poor knowledge	17 (42.5%)	23 (57.5%)	17.365	**<0.001**
Good knowledge	281 (73.9%)	99 (26.1%)		

*Fisher-Freeman-Halton exact test

In relation to religion, respondents identifying with Islam comprised the highest proportion with positive attitudes toward AI chatbots (80.2%), compared with respondents identifying with Christianity (66.7%) and other religions (71.4%). This association was statistically significant ($\chi^2 = 8.152$, $p = 0.013$), indicating a significant relationship between religion and attitudes toward AI chatbots for mental health support.

In relation to marital status, respondents who were never married comprised a substantially higher proportion with positive attitudes (72.2%) compared with those who were ever married (50.0%). This association was also statistically significant ($\chi^2 = 5.422$, $p = 0.020$), indicating a significant association between marital status and attitudes toward AI chatbots.

In relation to level of study, respondents in 600 level comprised the highest proportion with positive attitudes (88.6%), followed by 500 level students (78.7%) and 100 level students (76.7%), while 300 level respondents comprised the least proportion with positive attitudes (64.2%), closely followed by 200 level respondents (65.1%). This association was statistically significant ($\chi^2 = 11.735$, $p = 0.039$), indicating that level of study was significantly associated with respondents' attitudes toward AI chatbots.

In relation to level of knowledge, respondents classified as having good knowledge comprised a substantially higher proportion with positive attitudes (73.9%) compared with respondents with poor knowledge (42.5%). This association was highly statistically significant ($\chi^2 = 17.365$, $p < 0.001$), indicating that better knowledge of AI chatbots was significantly associated with more favorable attitudes toward their use for mental health support.

In relation to ethnicity, Edo and Non-Edo indigenes had nearly identical proportions of positive attitudes (71.6% and 70.2% respectively). However, this association was not statistically significant ($\chi^2 = 0.048$, $p = 0.826$), indicating no significant association between ethnicity and attitudes toward AI chatbots.

Similarly, all other variables examined, including age, gender, faculty, department, income, social class, and current living arrangement, were not statistically significantly associated with attitudes toward AI chatbots ($p > 0.05$).

Table 10: Predictors of Positive Attitudes towards AI chatbots

Predictors	β	Odds ratio	95% CI for OR		p-value
			Lower	Upper	
Age					
≤17*		1			
18–20	-2.215	0.109	0.014	0.872	**0.037**
21–23	-2.675	0.069	0.008	0.562	**0.012**
24–26	-2.728	0.065	0.008	0.561	**0.013**
≥27	-2.735	0.065	0.007	0.628	**0.018**
Gender					
Male *	—	1	—	—	—
Female	0.366	1.442	0.865	2.406	0.161
Religion					
Christianity*		1			
Islam	0.746	2.108	1.240	3.582	**0.006**
Others	0.327	1.387	0.24	7.807	0.711
Faculty					
Non-Medical *	—	1	—	—	—
Medical	0.086	1.090	0.037	32.275	0.960
Marital Status					
Never Married*		1			
Ever Married	-1.300	0.272	0.104	0.716	**0.008**
Level of Study					
100L*		1			
200L	0.000	1.000	0.363	2.752	0.100
300L	0.182	1.200	0.432	3.336	0.727
400L	0.705	2.023	0.672	6.088	0.210
500L	1.087	2.966	0.917	9.593	0.069
600L	2.068	7.908	1.748	35.783	**0.007**
Level of Knowledge					
Poor knowledge*		1			
Good knowledge	1.387	4.003	1.940	8.258	**<0.001**

*Reference category. Nagelkerke R^2 range: 0.201–0.222.

A backward stepwise logistic regression was conducted to identify sociodemographic predictors of positive attitudes toward AI chatbots for mental health support. The final model (Step 7) retained five significant independent predictors: age, religion, marital status, level of study, and level of knowledge.

Age was a significant predictor of attitude toward AI chatbots, with older respondents demonstrating significantly lower odds of positive attitudes compared with respondents aged ≤17 years. Respondents aged 18–20 years had 89.1% lower odds of positive attitudes (OR = 0.109; 95% CI: 0.014–0.872; $p = 0.037$). Similarly, those aged 21–23 years (OR = 0.069; 95% CI: 0.008–0.562; $p = 0.012$), 24–26 years (OR = 0.065; 95% CI: 0.008–0.561; $p = 0.013$), and ≥27 years (OR = 0.065; 95% CI: 0.007–0.628; $p = 0.018$) also had significantly reduced odds of exhibiting positive attitudes.

Religion was also a significant predictor of attitude. Respondents identifying with Islam had about twice the odds of exhibiting positive attitudes toward AI chatbots compared with those identifying with Christianity (OR = 2.108; 95% CI: 1.240–3.582; $p = 0.006$). However, respondents identifying with other religions did not differ significantly from the reference category ($p = 0.711$).

Marital status significantly predicted attitudes toward AI chatbots. Respondents who were ever married had 72.8% lower odds of positive attitudes compared with those never married (OR = 0.272; 95% CI: 0.104–0.716; $p = 0.008$).

Level of study was positively associated with attitudes toward AI chatbots, with increasing academic progression generally associated with higher odds of positive attitudes. This association reached statistical significance at 600 level, where respondents had nearly eight times higher odds of positive attitudes compared with 100 level students (OR = 7.908; 95% CI: 1.748–35.783; p = 0.007).

Level of knowledge was a strong positive predictor of attitude. Respondents with good knowledge had approximately four times higher odds of exhibiting positive attitudes compared with those with poor knowledge (OR = 4.003; 95% CI: 1.940–8.258; $p < 0.001$), indicating that better knowledge of AI chatbots significantly predicted more favorable attitudinal responses.

Gender, ethnicity, monthly income, socioeconomic class, and current living arrangement did not remain significant predictors and were sequentially excluded during stepwise model selection ($p > 0.05$). Faculty and department were excluded from the model due to multicollinearity.

SECTION D

Use of AI chatbots among respondents

Table 11: Uptake and Pattern of Utilisation of AI Chatbots

Variables	Frequency (n)	Percentage (%)
Uptake of AI Chatbots		
Have you ever used an AI Chatbot?		
Yes	401	96.6
No	14	3.4
Frequency of AI Chatbot Use (n = 401)		
How often do you use AI Chatbots?		
Very Rarely	10	2.4
Rarely	22	5.3
Sometimes	176	42.4
Often	127	30.6
Very Often	66	15.9
Average Daily Hours Spent on AI Chatbots (n = 401)		
I don't use them daily	114	27.5
30 minutes	86	20.7
1 hour	101	24.3
2 hours	71	17.1
> 2 hours	29	7.0
Pattern of utilization of AI chatbots		
AI Platforms Used (n = 401) *		
ChatGPT	359	86.5
Gemini	171	41.2
Meta AI (WhatsApp/Instagram)	156	37.6
Snapchat MyAI	40	9.6
Deepseek	9	2.2
Woebot	12	2.8
Wysa	8	1.8
Perplexity	1	0.2
Copilot	1	0.2
Purposes for AI Chatbot Use (n = 401) *		
Academic/School Work	390	94.0
Business/Work	225	54.2
To Unwind/Relax	73	17.6
Mental Health Support/Venting	52	12.5
Other[a]	12	2.9
Research	2	0.5

*Multiple response item [a]General life challenges, complex research, helping a friend, satisfying curiosity about various topics, holding a conversation, dumping emotional or family baggage, novel ideas, learning interesting things, seeking advice and controversial opinions, discussing personal interests and theories, and obtaining personal information.

In relation to uptake of AI chatbots, respondents who reported having used an AI chatbot at least once comprised the overwhelming bulk (96.6%) of the total respondents, while the least proportion (3.4%) had never used any AI chatbot, indicating near-universal adoption of AI chatbots among respondents.

In relation to frequency of use among respondents who had ever used AI chatbots, those who reported using them sometimes comprised the largest proportion (42.4%), followed by respondents who used them often (30.6%) and very often (15.9%), while the least proportions reported rarely (5.3%) and very rarely (2.4%) using them. This suggests that a substantial proportion of respondents engaged with AI chatbots on a regular basis.

In relation to average daily time spent using AI chatbots, respondents who reported not using them daily comprised slightly over one-quarter (27.5%) of users, while among daily users, those spending one hour per day comprised the largest proportion (24.3%), followed by those spending 30 minutes daily (20.7%) and two hours daily (17.1%). The least proportion (7.0%) reported spending more than two hours per day using AI chatbots.

In relation to AI platforms utilized, respondents who reported using ChatGPT comprised the overwhelming bulk (86.5%) of users, followed by Gemini (41.2%) and Meta AI (37.6%), while the least proportion reported use of Copilot and Perplexity (0.2%). These findings indicate that ChatGPT was by far the predominant AI chatbot platform used among respondents.

In relation to purpose of AI chatbot use, respondents who reported using AI chatbots for academic or school-related work comprised nearly all (94.0%) of users, representing the predominant purpose of use. This was followed by respondents using AI chatbots for business or work purposes (54.2%), while smaller proportions used them to unwind or relax (17.6%) or for mental health support and venting (12.5%). The least proportion used AI chatbots specifically for research purposes (0.5%). These findings suggest that utilization of AI chatbots among respondents was driven primarily by academic needs, with comparatively limited use for direct mental health support.

Table 12: Dependency on AI Chatbots (n = 401)

Variables	Frequency (n)	Percentage (%)
Indicators of AI Dependency		
Spent a lot of time thinking about AI or planning when to use it next		
Never	189	45.5
Rarely	127	30.6
Sometimes	64	15.4
Often	15	3.6
Always	6	1.4
Felt an urge to use AI more and more to feel satisfied		
Never	194	46.7
Rarely	95	22.9
Sometimes	72	17.3
Often	33	8.0
Always	7	1.7
Used AI to forget about personal problems or avoid real-life stress		
Never	204	49.2
Rarely	94	22.7
Sometimes	66	15.9
Often	26	6.3
Always	11	2.7
Tried to cut down on AI use without success		
Never	200	48.2
Rarely	117	28.2
Sometimes	60	14.5
Often	21	5.1
Always	3	0.7
Became restless or troubled if unable to access AI		
Never	223	53.7
Rarely	105	25.3
Sometimes	52	12.5
Often	17	4.1
Always	4	1.0
AI use has had a negative impact on studies or relationships		
Never	274	66.0
Rarely	69	16.6
Sometimes	41	9.9
Often	9	2.2
Always	8	1.9

In relation to preoccupation with AI use, respondents who reported never spending excessive time thinking about AI or planning its use comprised the largest proportion (45.5%) of users, followed by those who reported this rarely (30.6%), while only a small minority reported experiencing such behaviour frequently, suggesting generally low levels of preoccupation with AI use.

In relation to tolerance, respondents who reported never feeling an urge to use AI more intensively to achieve satisfaction comprised nearly half (46.7%) of users, while only a minority reported experiencing this often or always (8.0%), indicating low levels of tolerance-related dependency behaviour.

In relation to escapism through AI use, respondents who reported never using AI to avoid personal problems comprised almost half (49.2%) of respondents, while only a small minority reported doing so often (6.3%) or always (2.7%), suggesting that escapist use of AI chatbots was relatively uncommon.

In relation to attempts to cut down AI use, respondents who reported frequent failed attempts to reduce usage comprised only a small minority, with 5.1% reporting this often and 0.7% always, indicating that loss of control over AI use was generally infrequent.

Similarly, in relation to restlessness in the absence of AI access, only a small minority reported experiencing this often (4.1%) or always (1.0%), suggesting low levels of withdrawal-like dependency symptoms among respondents.

In relation to the negative impact of AI use on academic activities or interpersonal relationships, respondents who reported this had never occurred comprised the overwhelming majority (66.0%) of users, representing the most reassuring response profile among the dependency items, while only a minority (12.1%) reported such impacts occurring sometimes or more frequently.

Overall, responses across the dependency items suggest that the majority of respondents exhibited low or no dependency-related behaviours associated with AI chatbot use.

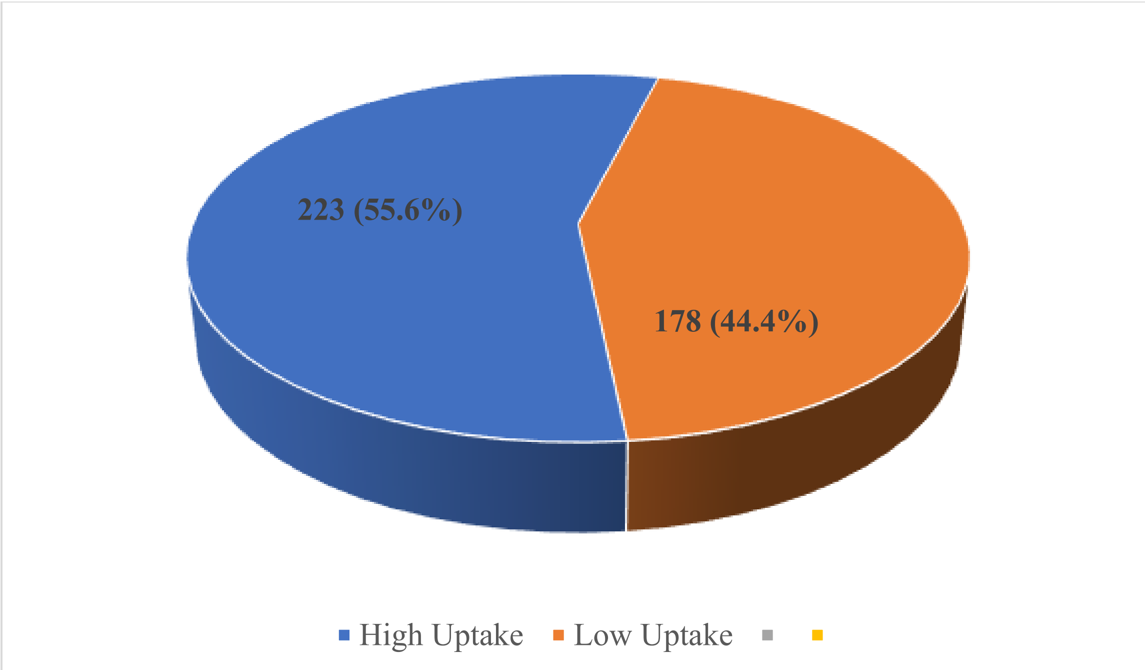

Figure 3: Level of Uptake of AI chatbots

More than half of the respondents were classified as having a high level of AI chatbot uptake (n = 223, 55.6%), while slightly less than half were classified as low uptake users (n = 178, 44.4%).

Table 13: Factors associated with Level of Uptake of AI chatbots

Variables	Level of Uptake		Test statistic	p-value
	High n (%)	Low n (%)		
Age				
< 18	12 (60.0%)	8 (40.0%)	2.558*	0.453
18 – 24	180 (56.8%)	137 (43.2%)		
25 – 30	27 (46.6%)	31 (53.4%)		
> 30	4 (66.7%)	2 (33.3%)		
Gender				
Male	124 (52.5%)	112 (47.5%)	2.188	0.153
Female	99 (60.0%)	66 (40.0%)		
Religion				
Christianity	159 (58.0%)	115 (42.0%)	3.377*	0.180
Islam	59 (49.2%)	61 (50.8%)		
Others	5 (71.4%)	2 (28.6%)		
Faculty				
Medical	144 (56.5%)	111 (43.5%)	.210	0.677
Non-Medical	79 (54.1%)	67 (45.9%)		
Department				
Medical	143 (56.3%)	111 (43.7%)	.133	0.755
Non-Medical	80 (54.4%)	67 (45.6%)		
Marital status				
Never married	211 (55.7%)	168 (44.3%)	.011	0.100
Ever married	12 (54.5%)	10 (45.5%)		
Ethnicity				
Edo indigenes	129 (59.7%)	87 (40.3%)	3.206	0.087
Non-Edo indigenes	94 (50.8%)	91 (49.2%)		
Level of study				
100L	11 (36.7%)	19 (63.3%)	9.637*	0.089
200L	64 (62.1%)	39 (37.9%)		
300L	57 (57.0%)	43 (43.0%)		
400L	37 (48.1%)	40 (51.9%)		
500L	32 (55.2%)	26 (44.8%)		
600L	22 (66.7%)	11 (33.3%)		
Socioeconomic class				
Lower	15 (37.5%)	25 (62.5%)	5.910*	0.055
Middle	153 (57.7%)	112 (42.3%)		
Upper	55 (57.3%)	41 (42.7%)		
Current living arrangement				
On campus	98 (51.0%)	94 (49.0%)	3.116	0.087
Off campus	125 (59.8%)	84 (40.2%)		

*Fisher-Freeman-Halton exact test.

Table 12 presents the distribution of AI chatbot uptake by sociodemographic characteristics among respondents ($n = 401$). A high level of uptake was observed across most sociodemographic categories; however, none of the variables examined attained statistical significance ($p > 0.05$).

Regarding age, the proportion of high uptake ranged from 46.6% among respondents aged 25 to 30 years ($n = 27$) to 66.7% among those aged over 30 years ($n = 4$), with no statistically significant association identified ($\chi^2 = 2.558$, $p = .453$). With respect to gender, female respondents recorded a higher proportion of high uptake ($n = 99$, 60.0%) than male respondents ($n = 124$, 52.5%), though this difference did not attain statistical significance ($\chi^2 = 2.188$, $p = 0.153$). Regarding religion, respondents identifying with other religious affiliations reported the highest proportion of high uptake ($n = 5$, 71.4%), followed by Christians ($n = 159$, 58.0%) and Muslims ($n = 59$, 49.2%); no statistically significant association was observed ($\chi^2 = 3.377$, $p = .180$).

In terms of level of study, the proportion of high uptake was lowest among 100L students ($n = 11$, 36.7%) and varied across academic levels, with 600L students recording the highest proportion ($n = 22$, 66.7%), followed by 200L ($n = 64$, 62.1%), 300L ($n = 57$, 57.0%), 500L ($n = 32$, 55.2%), and 400L students ($n = 37$, 48.1%). Despite this variation, no statistically significant association was identified between level of study and level of uptake ($\chi^2 = 9.637$, $p = .089$).

With respect to socioeconomic class, lower-class respondents recorded a notably lower proportion of high uptake ($n = 15$, 37.5%) compared to both middle-class ($n = 153$, 57.7%) and upper-class respondents ($n = 55$, 57.3%), with the association approaching but not attaining statistical significance ($\chi^2 = 5.910$, $p = .055$). Similarly, Edo indigene respondents demonstrated a higher proportion of high uptake ($n = 129$, 59.7%) compared to non-Edo indigenes ($n = 94$, 50.8%), though this difference was not statistically significant ($\chi^2 = 3.206$, $p = .087$). Respondents residing off campus recorded a higher proportion of high uptake ($n = 125$, 59.8%) than those residing on campus ($n = 98$, 51.0%), but the association likewise did not attain statistical significance ($\chi^2 = 3.116$, $p = .087$). All remaining variables including faculty, department and marital status were also not statistically significantly associated with the level of AI chatbot uptake ($p > .05$).

Table 14: Predictors of level of uptake of AI chatbots

Predictors	β	Odds ratio	95% CI for OR		p-value
			Lower	Upper	
Age					
< 18 years *	—	1	—	—	—
18 – 24 years	-0.449	0.639	0.219	1.863	0.412
25 – 30 years	-0.871	0.419	0.121	1.448	0.169
> 30 years	0.092	1.096	0.107	11.265	0.938
Religion					
Christianity *		1			
Islam	−.125	.882	.541	1.438	.615
Others	.474	1.606	.288	8.949	.589
Gender					
Male *	—	1	—	—	—
Female	0.201	1.222	0.784	1.905	0.376
Faculty					
Non-Medical *	—	1	—	—	—
Medical	0.327	1.386	0.113	16.983	0.798
Marital Status					
Never Married *	—	1	—	—	—
Ever Married	-0.067	0.936	0.331	2.645	0.900
Ethnicity					
Edo indigenes *		1			
Non-Edo indigenes	−.399	.671	.445	1.011	.056
Level of study					
100L *		1			
200L	1.119	3.062	1.294	7.246	.011
300L	.823	2.278	.967	5.365	.060
400L	.431	1.539	.633	3.739	.341
500L	.743	2.102	.834	5.300	.115
600L	1.373	3.947	1.362	11.439	.011
Socioeconomic class					
Lower *		1			
Middle	.877	2.403	1.187	4.863	.015
Upper	.946	2.577	1.176	5.646	.018
Current living arrangement					
On campus *		1			
Off campus	.460	1.585	1.044	2.404	.030

*Reference category. Nagelkerke R^2 range: 0.079–0.096.

A backward stepwise (conditional) logistic regression was performed to identify sociodemographic predictors independently associated with high uptake of AI chatbots. The initial full model included age, gender, religion, faculty, department, marital status, ethnicity, level of study, monthly income, socioeconomic class, and current living arrangement. After iteratively removing non-significant variables across eight elimination steps, the final model retained ethnicity, level of study, socioeconomic class, and current living arrangement. Variables removed during the backward elimination procedure were as follows: monthly income was removed at Step 2, marital status at Step 3, faculty at Step 4, department at Step 6, age at Step 7, and gender at Step 8.

Regarding religion, neither Muslim respondents (OR = 0.882, 95% CI: 0.541–1.438, $p = .615$) nor respondents in other religious categories (OR = 1.606, 95% CI: 0.288–8.949, $p = .589$) demonstrated a statistically significant difference in the odds of high uptake compared to Christian respondents.

Regarding ethnicity, non-Edo indigene respondents demonstrated lower odds of high AI chatbot uptake compared to Edo indigene respondents; however, this difference approached but did not attain conventional statistical significance in the final model (OR = 0.671, 95% CI: 0.445–1.011, $p = .056$).

Level of study proved to be a meaningful predictor of AI chatbot uptake. When compared to first-year students (100L), students in 200L demonstrated significantly higher odds of high uptake (OR = 3.062, 95% CI: 1.294–7.246, $p = .011$). Sixth-year students (600L) similarly exhibited significantly elevated odds relative to the 100L reference cohort (OR = 3.947, 95% CI: 1.362–11.439, $p = .011$). The odds for 300L students approached but did not attain significance (OR =

2.278, 95% CI: 0.967–5.365, p = .060), while those for 500L (OR = 2.102, 95% CI: 0.834–5.300, p = .115) and 400L students (OR = 1.539, 95% CI: 0.633–3.739, p = .341) did not significantly differ from the 100L reference group.

With respect to socioeconomic class, both middle-class (OR = 2.403, 95% CI: 1.187–4.863, p = .015) and upper-class respondents (OR = 2.577, 95% CI: 1.176–5.646, p = .018) demonstrated significantly greater odds of high uptake compared to lower-class respondents, indicating that higher socioeconomic standing was independently associated with increased uptake of AI chatbots. Regarding current living arrangement, respondents residing off campus demonstrated significantly higher odds of high AI chatbot uptake compared to those residing on campus (OR = 1.585, 95% CI: 1.044–2.404, p = .030). The variables age, gender, marital status, monthly income, and department were omitted from the table as they were found to be non-significant and were systematically removed during the stepwise elimination process prior to religion. Faculty and department represented largely overlapping respondent cohorts and may have contributed to multicollinearity prior to their respective eliminations.

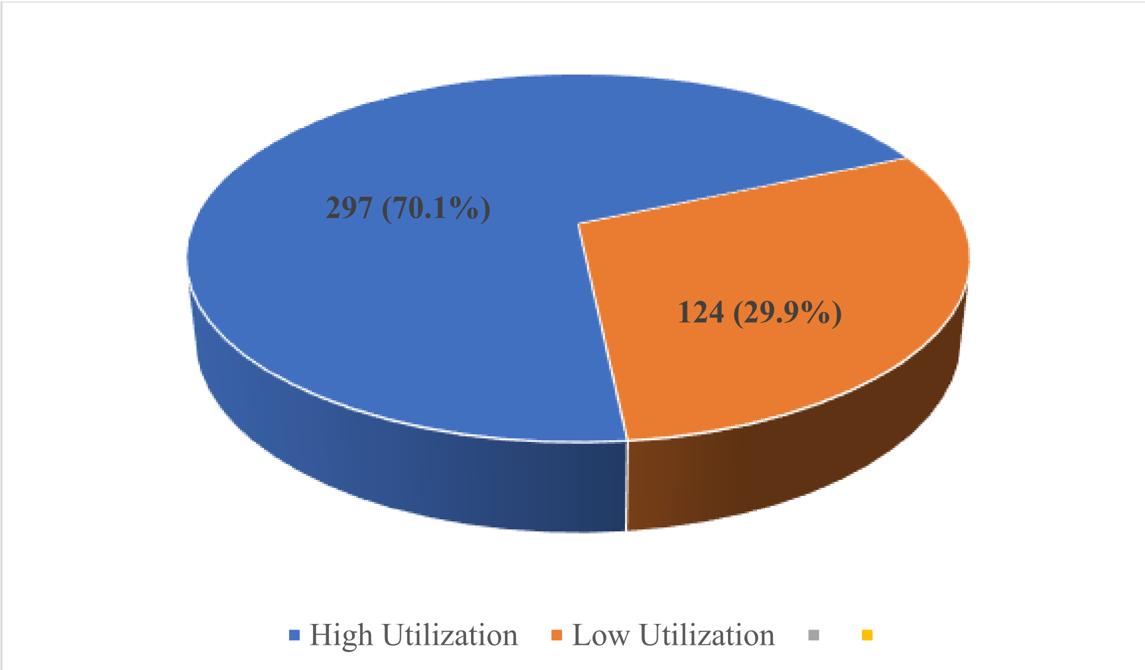

Figure 4: Level of Utilization of AI chatbots

The majority of respondents were classified as having a high level of AI chatbot utilisation (n = 291, 70.1%), while approximately three in ten were classified as low users (n = 124, 29.9%).

Table 15: Factors associated with Level of Utilisation of AI chatbots

Variables	Level of Utilization		Test statistic	p-value
	High Freq (%)	Low Freq (%)		
Age				
< 18	11 (52.4%)	10 (47.6%)	3.764	0.439
18 - 24	204 (64.6%)	112 (35.4%)		
25 - 30	34 (58.6%)	24 (41.4%)		
> 30	3 (50.0%)	3 (50.0%)		
Gender				
Male	150 (63.6%)	86 (36.4%)	0.126	0.723
Female	102 (61.8%)	63 (38.2%)		
Religion				
Christianity	162 (59.1%)	112 (40.9%)	5.585*	0.055
Islam	84 (70.0%)	36 (30.0%)		
Others	6 (85.7%)	1 (14.3%)		
Faculty				
Medical	155 (60.8%)	100 (39.2%)	1.271	0.260
Non-Medical	97 (66.4%)	49 (33.6%)		
Department				
Medical	154 (60.6%)	100 (39.4%)	1.453	0.228
Non-Medical	98 (66.7%)	49 (33.3%)		
Marital Status				
Never Married	237 (62.5%)	142 (37.5%)	0.284	0.594
Ever Married	15 (68.2%)	7 (31.8%)		
Ethnicity				
Edo indigenes	108 (50.0%)	108 (50.0%)	1.288	0.256
Non-Edo indigenes	103 (55.7%)	82 (44.3%)		
Level of study				
100L	13 (43.3%)	17 (56.7%)	15.054	**0.010**
200L	67 (65.0%)	36 (35.0%)		
300L	62 (62.0%)	38 (38.0%)		
400L	54 (70.1%)	23 (29.9%)		
500L	42 (72.4%)	16 (27.6%)		
600L	14 (42.4%)	19 (57.6%)		
Socioeconomic class				
Lower	24 (60.0%)	16 (40.0%)	0.495	0.781
Middle	165 (62.3%)	100 (37.7%)		
Upper	63 (65.6%)	33 (34.4%)		
Current living arrangement				
On campus	114 (59.4%)	78 (40.6%)	1.897	0.168
Off campus	138 (66.0%)	71 (34.0%)		
Level of Knowledge				
Poor knowledge	17 (54.8%)	14 (45.2%)	0.922	0.337
Good knowledge	235 (63.5%)	135 (36.5%)		
Level of Attitude				
Negative attitude	60 (55.0%)	49 (45.0%)	3.897	**0.048**
Positive attitude	192 (65.8%)	100 (34.2%)		

*Fisher-Freeman-Halton exact test.

With respect to Level of study, there was a statistically significant association with the level of AI chatbot utilisation ($\chi^2 = 15.054$, $p = 0.010$). Detailed analysis reveals a clear trend where the proportion of respondents reporting high utilisation generally increased as students progressed from their first year up to their fifth year. Specifically, 500L students reported the highest proportion of high usage at 72.4% (n = 42), followed by 400L students at 70.1% (n = 54), 200L students at 65.0% (n = 67), and 300L students at 62.0% (n = 62). In contrast, the lowest proportions of high usage were observed at the beginning and end of the academic progression: 100L students at 43.3% (n = 13) and 600L students at 42.4% (n = 14).

Regarding Level of Attitude, respondents with a positive attitude had a higher proportion of high utilisation (n = 192, 65.8%) compared to those with a negative attitude (n = 60, 55.0%). This association was statistically significant ($\chi^2 = 3.897$, $p = 0.048$), suggesting that respondents who held more favourable attitudes towards AI chatbots were more likely to be classified as high users.

All other variables, including Age, Gender, Religion, Faculty, Department, Marital Status, Ethnicity, Socioeconomic Class, and Current living arrangement, were not statistically significantly associated with utilisation levels ($p > 0.05$).

Table 16: Predictors of level of utilisation of AI chatbots

Predictors	β	Odds ratio	95% CI for OR		p-value
			Lower	Upper	
Age					
< 18 years *	—	1	—	—	—
18 – 24 years	0.508	1.661	0.579	4.766	0.345
25 – 30 years	0.368	1.444	0.476	4.381	0.516
> 30 years	0.440	1.552	0.458	5.260	0.480
Gender					
Male *	—	1	—	—	—
Female	0.037	1.038	0.643	1.673	0.880
Religion					
Christianity *		1			
Islam	0.501	1.650	1.025	2.656	**0.039**
Others	1.498	4.472	0.517	38.712	0.174
Faculty					
Non-Medical *	—	1	—	—	—
Medical	1.238	3.449	0.247	48.089	0.357
Level of study					
100L *		1			
200L	0.941	2.563	1.106	5.936	**0.028**
300L	0.877	2.405	1.032	5.604	**0.042**
400L	1.202	3.327	1.377	8.040	**0.008**
500L	1.292	3.641	1.430	9.270	**0.007**
600L	0.048	1.049	0.379	2.901	0.926

*Reference category. Nagelkerke R^2 range: 0.082–0.125

A backward stepwise (conditional) logistic regression was performed to identify the sociodemographic predictors associated with high utilisation of AI chatbots. The initial full model included age, gender, religion, faculty, department, marital status, ethnicity, level of study, monthly income, socioeconomic class, current living arrangement, level of knowledge, and level of attitude. After iteratively removing non-significant variables across eleven elimination steps, the final model retained Religion and Level of Study as the sole significant predictive factors. Level of Knowledge and Level of Attitude were both included in the initial model but were eliminated during the backward stepwise procedure, indicating that they did not independently contribute significant predictive power to utilisation levels when controlling for other variables.

Regarding religion, the model revealed that students practicing Islam demonstrated a statistically significant increase in the odds of high AI chatbot usage when compared to Christian students (OR = 1.650, 95% CI: 1.025 – 2.656, p = 0.039). The "Others" religious category also indicated higher odds compared to the reference group, though this difference was not statistically significant (OR = 4.472, 95% CI: 0.517 – 38.712, p = 0.174).

Level of study proved to be a strong positive predictor of AI chatbot usage. When compared to first-year students (100L), students in higher academic levels showed significantly greater odds of reporting high usage. Specifically, 500L students exhibited the highest likelihood of high usage (OR = 3.641, 95% CI: 1.430 – 9.270, p = 0.007), closely followed by 400L students (OR = 3.327, 95% CI: 1.377 – 8.040, p = 0.008). Students in 200L (OR = 2.563, 95% CI: 1.106 – 5.936, p = 0.028) and 300L (OR = 2.405, 95% CI: 1.032 – 5.604, p = 0.042) also exhibited significantly higher odds of high usage than 100L students. However, the odds for 600L students did not significantly differ from the 100L reference cohort (OR = 1.049, 95% CI: 0.379 – 2.901, p = 0.926).

The variables Age, Gender, Marital Status, Ethnicity, Monthly Income, Socioeconomic Class, Current Living Arrangement, Level of Knowledge, and Level of Attitude were strictly omitted from the table because they were found to be non-significant and systematically removed during the stepwise elimination process. The variables Faculty and Department were omitted from the table because they exhibited severe multicollinearity (representing nearly identical respondent cohorts), which manifested as heavily inflated standard errors prior to their respective eliminations.

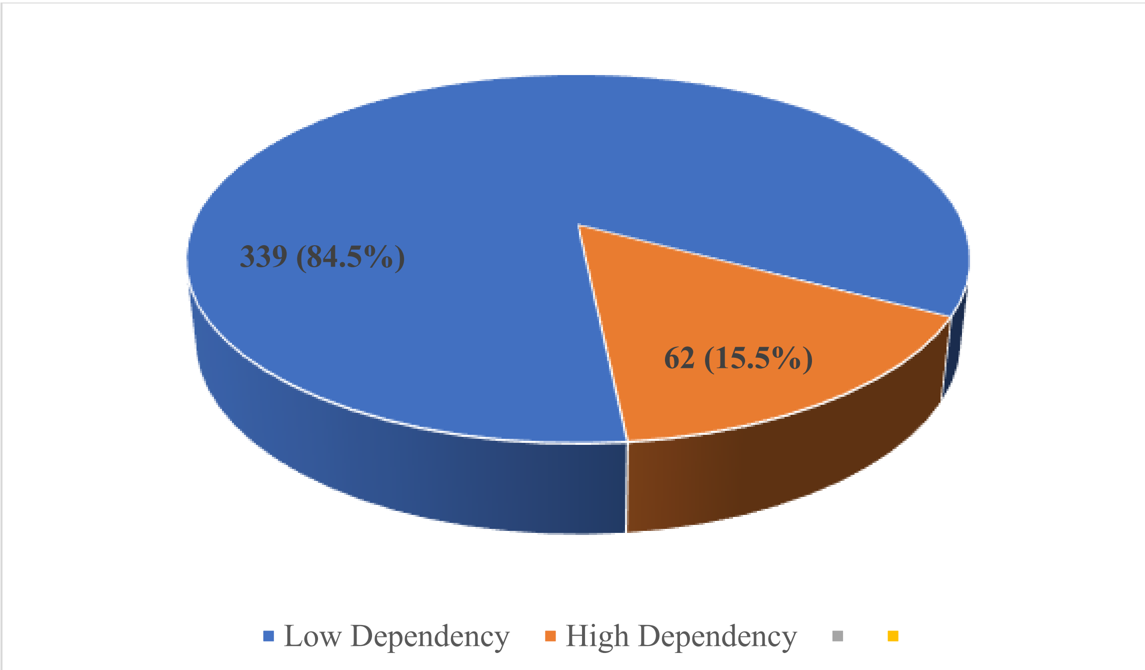

Figure 5: Level of Dependency on AI chatbots

The large majority of respondents were classified as having a low level of AI chatbot dependency (n = 339, 84.5%), while a minority were classified as having a high level of dependency (n = 62, 15.5%).

Table 17: Factors associated with Level of Dependency on AI chatbots

Variables	Dependency		Test statistic	p-value
	Low n (%)	High n (%)		
Age (years)				
< 18	17 (85.0%)	3 (15.0%)	4.221*	.185
18 – 24	273 (86.1%)	44 (13.9%)		
25 – 30	45 (77.6%)	13 (22.4%)		
> 30	4 (66.7%)	2 (33.3%)		
Gender				
Male	195 (82.6%)	41 (17.4%)	1.603	.211
Female	144 (87.3%)	21 (12.7%)		
Religion				
Christianity	244 (89.1%)	30 (10.9%)	15.245*	.001**
Islam	91 (75.8%)	29 (24.2%)		
Others	4 (57.1%)	3 (42.9%)		
Faculty				
Medical	221 (86.7%)	34 (13.3%)	2.426	.151
Non-Medical	118 (80.8%)	28 (19.2%)		
Department				
Medical	220 (86.6%)	34 (13.4%)	2.284	.152
Non-Medical	119 (81.0%)	28 (19.0%)		
Marital status				
Never married	323 (85.2%)	56 (14.8%)	2.484	.128
Ever married	16 (72.7%)	6 (27.3%)		
Ethnicity				
Edo indigenes	192 (88.9%)	24 (11.1%)	6.779	.012*
Non-Edo indigenes	147 (79.5%)	38 (20.5%)		
Level of study				
100L	26 (86.7%)	4 (13.3%)	9.461*	.082
200L	81 (78.6%)	22 (21.4%)		
300L	92 (92.0%)	8 (8.0%)		
400L	64 (83.1%)	13 (16.9%)		
500L	46 (79.3%)	12 (20.7%)		
600L	30 (90.9%)	3 (9.1%)		
Socioeconomic class				
Lower	31 (77.5%)	9 (22.5%)	3.340*	.174
Middle	230 (86.8%)	35 (13.2%)		
Upper	78 (81.3%)	18 (18.8%)		
Current living arrangement				
On campus	163 (84.9%)	29 (15.1%)	.036	.891
Off campus	176 (84.2%)	33 (15.8%)		

*Fisher-Freeman-Halton exact test. **p < .010.

Table 16 presents the distribution of AI chatbot dependency levels by sociodemographic characteristics among respondents (n = 401). High dependency was observed in a minority of respondents across all sociodemographic categories. Of all variables examined, religion and ethnicity were the only factors that attained statistical significance.

Regarding religion, a statistically significant association was identified between religious affiliation and level of AI chatbot dependency ($\chi^2 = 15.245$, $p = .001$). Respondents identifying with other religious affiliations reported the highest proportion of high dependency (n = 3, 42.9%), followed by Muslims (n = 29, 24.2%) and Christians (n = 30, 10.9%). This distribution indicates a notably elevated risk of high dependency among Muslim respondents and among those in other religious categories relative to their Christian counterparts.

In terms of ethnicity, non-Edo indigene respondents demonstrated a substantially higher proportion of high dependency (n = 38, 20.5%) compared to Edo indigenes (n = 24, 11.1%), and this association was statistically significant ($\chi^2 = 6.779$, $p = .012$).

With respect to age, the proportion of high dependency was lowest among respondents aged 18 to 24 years (n = 44, 13.9%) and highest among those aged over 30 years (n = 2, 33.3%), though no statistically significant association was identified ($\chi^2 = 4.221$, $p = .185$). Regarding gender, male respondents recorded a higher proportion of high dependency (n = 41, 17.4%) compared to female respondents (n = 21, 12.7%), though this difference was not statistically significant ($\chi^2 = 1.603$, $p = .211$). Among level of study subgroups, 200L students recorded the highest proportion of high dependency (n = 22, 21.4%), followed by 500L students (n = 12, 20.7%), while 600L students had the lowest proportion (n = 3, 9.1%) and 300L students the second lowest (n = 8, 8.0%). Despite this variation, no statistically significant association was found between level of study and dependency level ($\chi^2 = 9.461$, $p = .082$). All other variables including faculty, department, marital status, monthly income, socioeconomic class, and current living arrangement were also not statistically significantly associated with the level of AI chatbot dependency ($p > 0.05$).

Table 18: Predictors of level of dependency on AI chatbots

Predictors	β	Odds ratio	95% CI for OR		p-value
			Lower	Upper	
Age (years)					
< 18 years *	—	1	—	—	—
18 – 24 years	0.173	1.189	0.293	4.830	0.809
25 – 30 years	0.773	2.166	0.436	10.777	0.345
> 30 years	0.903	2.467	0.190	32.018	0.490
Gender					
Male *	—	1	—	—	—
Female	-0.273	0.761	0.400	1.450	0.406
Religion					
Christianity *		1			
Islam	.818	2.265	1.267	4.051	.006
Others	1.807	6.095	1.282	28.968	.023
Faculty					
Non-Medical *	—	1	—	—	—
Medical	0.616	1.852	0.054	63.497	0.733
Ethnicity					
Edo indigenes *		1			
Non-Edo indigenes	.563	1.756	.986	3.128	.056
Level of Study					
100 Level *	—	1	—	—	—
200 Level	0.691	1.996	0.610	6.526	0.253
300 Level	-0.347	0.707	0.191	2.620	0.604
400 Level	0.484	1.623	0.471	5.593	0.443
500 Level	0.697	2.008	0.569	7.082	0.278
600 Level	-0.213	0.808	0.159	4.105	0.797
Socioeconomic Class					
Lower Class *	—	1	—	—	—
Middle Class	-0.128	0.880	0.352	2.200	0.785
Upper Class	0.461	1.586	0.554	4.541	0.390
Current Living Arrangement					
On-campus *	—	1	—	—	—
Off-campus	-0.154	0.857	0.471	1.558	0.613

*Reference category. Nagelkerke R^2 range: 0.074–0.143

A backward stepwise (conditional) logistic regression was performed to identify sociodemographic predictors independently associated with high AI chatbot dependency. The initial full model included age, gender, religion, faculty, department, marital status, ethnicity, level of study, monthly income, socioeconomic class, and current living arrangement. After iteratively removing non-significant variables across ten elimination steps, the final model retained only religion level of study and ethnicity. Variables removed during the backward elimination procedure were as follows: monthly income was removed at Step 2, faculty at Step 3, current living arrangement at Step 4, age at Step 5, department at Step 6, socioeconomic class at Step 7, marital status at Step 8 and gender at Step 9.

Regarding level of study, none of the academic levels differed significantly from 100L students in the odds of high dependency: 200L (OR = 1.996, 95% CI: 0.610–6.526, $p = .253$), 300L (OR = 0.707, 95% CI: 0.191–2.620, $p = .604$), 400L (OR = 1.623, 95% CI: 0.471–5.593, $p = .443$), 500L (OR = 2.008, 95% CI: 0.569–7.082, $p = .278$), or 600L (OR = 0.808, 95% CI: 0.159–4.105, $p = .797$).

Regarding religion, Muslim respondents demonstrated significantly greater odds of high AI chatbot dependency compared to Christian respondents, who served as the reference category (OR = 2.265, 95% CI: 1.267–4.051, $p = .006$). Respondents identifying with other religious affiliations also exhibited markedly elevated odds of high dependency relative to Christians, and this association attained statistical significance (OR = 6.095, 95% CI: 1.282–28.968, $p = .023$), though the wide confidence interval reflects the small number of respondents in this category ($n = 7$) and warrants cautious interpretation.

Regarding ethnicity, non-Edo indigene respondents demonstrated higher odds of high dependency compared to Edo indigenes; however, this difference approached but did not attain conventional statistical significance in the final model (OR = 1.756, 95% CI: 0.986–3.128, $p = .056$). This finding nevertheless corroborates the significant bivariate association observed in the chi-square analysis and suggests a trend worthy of attention in future research with larger samples.

The variables age, gender, marital status, faculty, department, monthly income, socioeconomic class, and current living arrangement were omitted from the table as they were found to be non-significant and were systematically removed from the model prior to religion, ethnicity, and level of study during the stepwise elimination process.

SECTION E

Mental health status of respondents

Table 19: Mental health symptoms among respondents

Variables	Not at all Freq (%)	Several days Freq (%)	More than half the days Freq (%)	Nearly every day Freq (%)
Over the last 2 weeks, how often have you been bothered by any of the following problems?				
Little interest or pleasure in doing things	169 (42.1%)	153 (38.2%)	47 (11.7%)	32 (8.0%)
Feeling down, depressed, or hopeless	179 (44.6%)	158 (39.4%)	40 (10.0%)	24 (6.0%)
Trouble falling or staying asleep, or sleeping too much	185 (46.1%)	131 (32.7%)	57 (14.2%)	28 (7.0%)
Feeling tired or having little energy	118 (29.4%)	170 (42.4%)	75 (18.7%)	38 (9.5%)
Poor appetite or overeating	219 (54.6%)	128 (31.9%)	36 (9.0%)	18 (4.5%)
Feeling bad about yourself or that you are a failure	216 (53.9%)	128 (31.9%)	40 (10.0%)	17 (4.2%)
Trouble concentrating on things	199 (49.6%)	137 (34.2%)	46 (11.5%)	19 (4.7%)
Moving or speaking so slowly, or being fidgety/restless	250 (62.3%)	119 (29.7%)	25 (6.2%)	7 (1.7%)
Thoughts of being better off dead or of hurting yourself	276 (68.8%)	98 (24.4%)	14 (3.5%)	13 (3.2%)
Associated functional impairment				
Difficulty working	152 (37.9%)	213 (53.1%)	29 (7.2%)	7 (1.7%)
Difficulty taking care of things at home	185 (46.1%)	197 (49.1%)	17 (4.2%)	2 (0.5%)
Difficulty getting along with other people	181 (45.1%)	168 (41.9%)	40 (10.0%)	12 (3.0%)

Table 18 presents mental health symptoms and associated functional impairment among respondents. In relation to mental health symptoms experienced by respondents, fatigue (feeling tired or having little energy) was the most frequently reported symptom, with respondents reporting at least some occurrence comprising over two-thirds (70.6%) of the total respondents, while only 29.4% reported no occurrence. This was followed by anhedonia, with 57.9% reporting some occurrence, and depressed mood, reported by 55.4% of respondents, indicating that emotional distress and low energy were prominent symptoms among respondents.

In relation to other commonly reported symptoms, respondents reporting some degree of sleep disturbance comprised over half (53.9%) of the respondents, while trouble concentrating was reported by slightly over half (50.4%). Similarly, respondents reporting feelings of worthlessness or failure comprised 46.1%, while poor appetite or overeating was reported by 45.4%, suggesting a considerable burden of cognitive and affective symptoms among respondents.

In relation to less frequently reported symptoms, respondents who reported no occurrence of psychomotor disturbance comprised the majority (62.3%), while respondents reporting no occurrence of passive suicidal ideation comprised the overwhelming bulk (68.8%), making it the least frequently endorsed symptom. However, nearly one-third (31.2%) of respondents reported some occurrence of suicidal ideation, representing a notable proportion warranting concern.

In relation to functional impairment associated with mental health symptoms, respondents reporting at least some difficulty with work performance comprised the majority (62.1%), representing the most affected functional domain. This was followed by interpersonal functioning, where 54.9% reported some degree of difficulty getting along with others. Respondents reporting impairment in home management comprised 53.9%, although this represented the least affected functional domain among the three domains assessed.

Overall, the findings suggest that while fatigue, anhedonia, depressed mood, and sleep-related symptoms were the most commonly experienced mental health symptoms, these symptoms were also associated with notable functional impairment, particularly in work performance and interpersonal functioning.

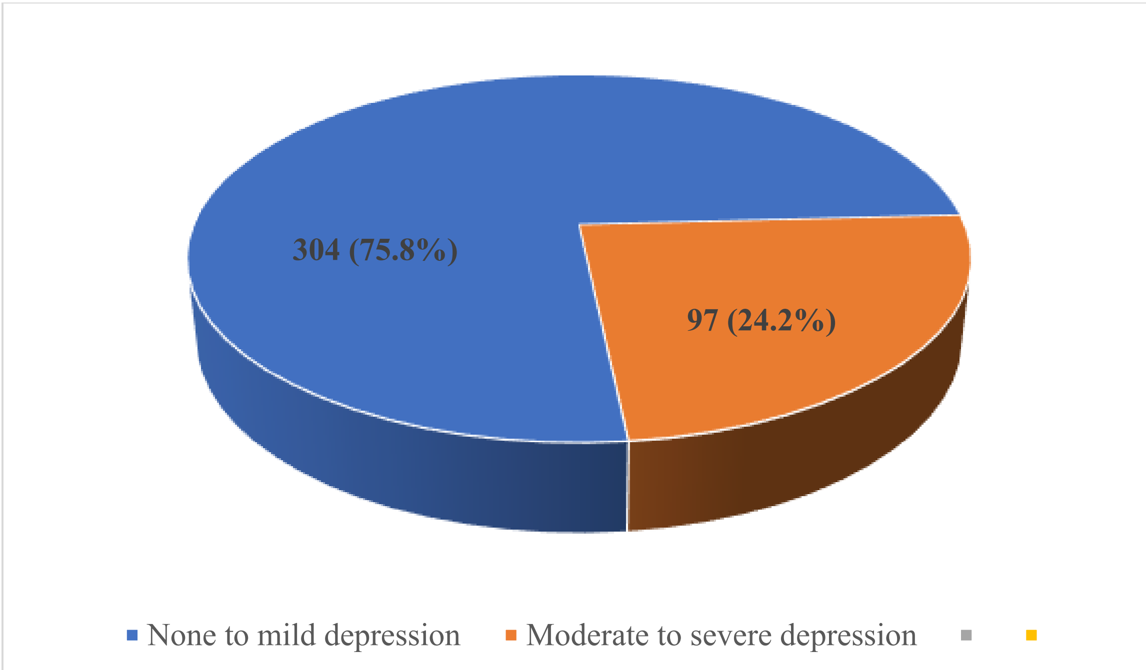

Figure 6: Mental health status among respondents

Of the 401 respondents included in the analysis, 240 (59.9%) screened positive for depression, while 161 (40.1%) did not.

Table 20: Factors Associated with Prevalence of Depression

Variable	Category	Prevalence of Depression		χ²	p-value
		Not Depressed n(%)	Depressed n(%)		
Age (years)	< 18	12 (60.0%)	8 (40.0%)	12.256	0.005**
	18 – 24	115 (36.3%)	202 (63.7%)		
	25 – 30	29 (50.0%)	29 (50.0%)		
	> 30	5 (83.3%)	1 (16.7%)		
Gender	Male	91 (38.6%)	145 (61.4%)	0.604	0.469
	Female	70 (42.4%)	95 (57.6%)		
Religion	Christianity	117 (42.7%)	157 (57.3%)	2.551	0.287
	Islam	41 (34.2%)	79 (65.8%)		
	Others	3 (42.9%)	4 (57.1%)		
Faculty	Non-Medical	50 (34.2%)	96 (65.8%)	3.329	0.073
	Medical	111 (43.5%)	144 (56.5%)		
Department	Non-Medical	50 (34.0%)	97 (66.0%)	3.636	0.058
	Medical	111 (43.7%)	143 (56.3%)		
Marital Status	Never Married	149 (39.3%)	230 (60.7%)	2.007	0.182
	Ever Married	12 (54.5%)	10 (45.5%)		
Ethnicity	Edo indigenes	88 (40.7%)	128 (59.3%)	0.068	0.838
	Non-Edo indigenes	73 (39.5%)	112 (60.5%)		
Level of Study	100L	13 (43.3%)	17 (56.7%)	19.959	0.001**
	200L	31 (30.1%)	72 (69.9%)		
	300L	38 (38.0%)	62 (62.0%)		
	400L	37 (48.1%)	40 (51.9%)		
	500L	19 (32.8%)	39 (67.2%)		
	600L	23 (69.7%)	10 (30.3%)		
Monthly Income	< ₦77,000	124 (38.0%)	202 (62.0%)	3.238	0.089
	≥ ₦77,000	37 (49.3%)	38 (50.7%)		
Socioeconomic Class	Lower	14 (35.0%)	26 (65.0%)	0.749	0.676
	Middle	110 (41.5%)	155 (58.5%)		
	Upper	37 (38.5%)	59 (61.5%)		
Current Living Arrangement	On campus	67 (34.9%)	125 (65.1%)	4.232	0.042*
	Off campus	94 (45.0%)	115 (55.0%)		
Knowledge Level	Poor knowledge	12 (38.7%)	19 (61.3%)	0.029	0.100
	Good knowledge	149 (40.3%)	221 (59.7%)		
Attitude Level	Negative attitude	41 (37.6%)	68 (62.4%)	0.400	0.568
	Positive attitude	120 (41.1%)	172 (58.9%)		
Level of Uptake	Low Uptake	65 (36.5%)	113 (63.5%)	1.758	0.219
	High Uptake	96 (43.0%)	127 (57.0%)		
Level of Dependency	Low	147 (43.4%)	192 (56.6%)	9.421	0.003**
	High	14 (22.6%)	48 (77.4%)		
Usage Level	Low	91 (47.9%)	99 (52.1%)	9.014	0.003**
	High	70 (33.2%)	141 (66.8%)		

Table 19 presents the bivariate associations between respondent characteristics and the prevalence of depression ($n = 401$). A total of 240 respondents (59.9%) screened positive for depression, while 161 (40.1%) did not.

In relation to age, respondents aged 18–24 years comprised the highest proportion who screened positive for depression (63.7%), while respondents aged >30 years comprised the least proportion with depression (16.7%). This association was statistically significant ($\chi^2 = 12.256$, $p = 0.005$), indicating a significant relationship between age and depression among respondents.

In relation to gender, male respondents comprised a slightly higher proportion who screened positive for depression (61.4%) compared with female respondents (57.6%). However, this association was not statistically significant ($\chi^2 = 0.604$, $p = 0.469$), indicating no significant association between gender and depression.

In relation to religion, respondents identifying with Islam comprised the highest proportion with depression (65.8%), followed by respondents in other religions (57.1%) and Christianity (57.3%). However, this association was not statistically significant ($\chi^2 = 2.551$, $p = 0.287$).

In relation to faculty and department, respondents in non-medical disciplines comprised higher proportions with depression than their medical counterparts. However, neither faculty ($\chi^2 = 3.329$, $p = 0.073$) nor department ($\chi^2 = 3.636$, $p = 0.058$) showed statistically significant associations with depression.

In relation to marital status and ethnicity, although never-married respondents comprised a higher proportion with depression (60.7%) compared with ever-married respondents (45.5%), and depression prevalence was comparable between Edo (59.3%) and Non-Edo indigenes (60.5%), neither association was statistically significant ($p > 0.05$).

In relation to level of study, respondents in 200 level comprised the highest proportion with depression (69.9%), followed by 500 level respondents (67.2%), while 600 level respondents comprised the least proportion with depression (30.3%) and were the only group in which the majority screened negative for depression. This association was statistically significant (χ^2 = 19.959, p = 0.001), indicating that level of study was significantly associated with depression.

Monthly income and socioeconomic class were not statistically significantly associated with depression ($p > 0.05$).

In relation to current living arrangement, respondents residing on campus comprised a higher proportion with depression (65.1%) compared with those living off campus (55.0%). This association was statistically significant (χ^2 = 4.232, p = 0.042), indicating a significant association between living arrangement and depression.

Knowledge level, attitude level, and level of uptake were not statistically significantly associated with depression ($p > 0.05$).

However, in relation to level of dependency, respondents classified as having high dependency comprised a substantially higher proportion with depression (77.4%) compared with respondents with low dependency (56.6%). This association was statistically significant (χ^2 = 9.421, p = 0.003), indicating a significant association between AI dependency and depression.

Similarly, respondents with high usage comprised a higher proportion with depression (66.8%) compared with respondents with low usage (52.1%). This association was also statistically significant (χ^2 = 9.014, p = 0.003), indicating a significant association between AI chatbot usage level and depression.

Table 21: Predictors of Prevalence of Depression

Variable	Categories	β	Odds Ratio (OR)	95% CI for OR	p-value
Age (years)	< 18*		1		
	18 – 24	1.324	3.759	1.331 – 10.620	0.012
	25 – 30	0.944	2.569	0.774 – 8.529	0.123
	> 30	-0.765	0.465	0.036 – 6.015	0.558
Department	Non-Medical*		1		
	Medical	-0.405	0.667	0.414 – 1.074	0.095
Level of Study	100L*		1		
	200L	0.382	1.465	0.577 – 3.721	0.422
	300L	-0.054	0.948	0.367 – 2.448	0.912
	400L	-0.570	0.566	0.211 – 1.513	0.256
	500L	0.078	1.081	0.379 – 3.083	0.884
	600L	-1.105	0.331	0.101 – 1.091	0.069
Socioeconomic Class	Lower Class *	—	1	—	—
	Middle Class	-0.165	0.848	0.384 – 1.875	0.684
	Upper Class	-0.111	0.895	0.362 – 2.212	0.810
Gender	Male *	—	1	—	—
	Female	-0.173	0.841	0.523 – 1.351	0.473
Current Living Arrangement	On campus*		1		
	Off campus	-0.515	0.597	0.382 – 0.933	0.024
Level of Knowledge	Poor Knowledge *	—	1	—	—
	Good Knowledge	0.339	1.404	0.599 – 3.293	3.293
Level of Utilization	Low*		1		
	High	0.561	1.753	1.083 – 2.836	0.022
Level of Uptake	Low*		1		
	High	-0.469	0.626	0.395 – 0.990	0.045
Level of Dependency	Low*		1		
	High	0.776	2.173	1.039 – 4.542	0.039

* = Reference Category. Nagelkerke R^2 range: 0.173–0.185.

The backward stepwise binary logistic regression identified Age, Department, Level of Study, Current Living Arrangement, Usage Level, Level of Uptake, and Level of Dependency as variables retained in the final model (Step 10). The model demonstrated good fit (Hosmer–Lemeshow χ^2 = 5.305, df = 8, p = 0.725; Nagelkerke R^2 = 0.173) and correctly classified 66.6% of cases overall.

Regarding Age, respondents aged 18–24 years had significantly higher odds of depression compared to those aged <18 years (OR = 3.759, 95% CI: 1.331–10.620, p = 0.012). The odds ratios for respondents aged 25–30 years (OR = 2.569, p = 0.123) and >30 years (OR = 0.465, p = 0.558) were not individually significant.

For Department, although Medical department students had lower odds of depression compared to Non-Medical students (OR = 0.667, 95% CI: 0.414–1.074), this individual coefficient did not reach statistical significance ($p = 0.095$); the variable was retained in the model by the stepwise procedure.

Level of Study was retained in the final model with an overall significant effect (Wald = 14.100, df = 5, $p = 0.015$). None of the individual level contrasted against 100L reached statistical significance independently, though the pattern consistently showed lower odds of depression at higher levels of study, particularly 600L (OR = 0.331, $p = 0.069$).

With respect to Current Living Arrangement, respondents living off campus had significantly lower odds of depression compared to those residing on campus (OR = 0.597, 95% CI: 0.382–0.933, $p = 0.024$), suggesting a protective effect of off-campus living.

Level of utilization was a significant predictor of depression. Respondents with high usage of AI chatbots had significantly higher odds of screening positive for depression compared to those with low usage (OR = 1.753, 95% CI: 1.083–2.836, $p = 0.022$). Conversely, Level of Uptake showed a positive association as respondents with high uptake had significantly lower odds of depression than those with low uptake (OR = 0.626, 95% CI: 0.395–0.990, $p = 0.045$).

Level of Dependency was a significant predictor of depression. Respondents classified as having high dependency on AI chatbots had more than twice the odds of screening positive for depression compared to those with low dependency (OR = 2.173, 95% CI: 1.039–4.542, $p = 0.039$).

The variables Gender, Religion, Marital Status, Ethnicity, Monthly Income, Socioeconomic Class, Knowledge Level, and Attitude Level were excluded from the final model as they were non-significant and were systematically eliminated during the backward stepwise procedure.

SECTION F

Factors influencing the use of AI chatbots among respondents

Table 22: Factors Influencing the Use of AI Chatbots (n = 401)

Variables	Frequency (n)	Percentage (%)
Family member who has suffered from mental health challenges		
Yes	113	28.2
No	188	71.8
Friend/peer who uses AI tools for emotional support		
Yes	150	37.4
No	251	62.6
Ever been encouraged by friends to try an AI Chatbot		
Yes	242	60.3
No	159	39.7
Factors Discouraging AI Chatbot Use *		
Prefer human connection/empathy over robots	188	46.9
Unstable electricity/power to charge device	136	33.9
Fear that data/secrets will be leaked	135	33.7
High cost of internet data subscription	134	33.4
Do not know how to use these tools	24	6.0
Religious beliefs against AI	10	2.5
Factors Encouraging AI Chatbot Use *		
24/7 Availability (especially late at night)	230	57.4
Instant response time	190	47.4
Anonymity (nobody will know I have a problem)	166	41.4
Cheaper/Free compared to traditional therapy	155	38.7

*Multiple response item. α = 0.733

Table 21 presents data on the social, contextual, and structural factors influencing AI chatbot use among respondents. The variables assessed include family mental health history, peer AI engagement, social encouragement, and self-reported barriers and facilitators to AI chatbot adoption.

In relation to family history of mental health challenges, respondents who reported no family history comprised the majority (71.8%) of the total respondents, while 28.2% confirmed that a family member had experienced mental health challenges.

In relation to peer influence, respondents who reported awareness of a friend or peer using AI tools for emotional support comprised over one-third (37.4%) of respondents, while the majority (62.6%) reported no awareness or were unsure. Similarly, respondents who reported having been encouraged by friends to try an AI chatbot comprised over three-fifths (60.3%) of respondents, while 39.7% had not received such encouragement, suggesting peer influence as a notable factor in AI chatbot use.

In relation to barriers discouraging AI chatbot use, respondents who cited preference for human connection and empathy over robots comprised the largest proportion (46.9%), making it the most frequently reported barrier. This was followed by unstable electricity or difficulty charging devices (33.9%), fear of data privacy breaches (33.7%), and high cost of internet data subscriptions (33.4%), each reported by approximately one-third of respondents. The least frequently reported barriers were not knowing how to use AI chatbots (6.0%) and religious beliefs against AI (2.5%).

In relation to factors encouraging AI chatbot use, respondents who identified round-the-clock availability as a facilitator comprised the majority (57.4%), representing the most frequently endorsed encouraging factor. This was followed by instant response time (47.4%), anonymity (41.4%), and lower cost compared with traditional therapy services (38.7%). These findings indicate that convenience, accessibility, privacy, and affordability were major factors encouraging AI chatbot use among respondents.

Overall, the findings suggest that social influence, perceived utility, structural barriers, and accessibility-related facilitators all played important roles in shaping respondents' use of AI chatbots.

Table 23: Association between level of uptake and factors influencing use of AI chatbots among respondents.

Variables	Level of Uptake		χ^2	p-Value
	High n (%)	Low n (%)		
Family member who has suffered from mental health challenges				
Yes	64 (56.6%)	49 (43.4%)	2.728	0.256
No/Not sure	159 (55.2%)	129 (44.8%)		
Peer Influence				
Yes	93 (62.0%)	57 (38.0%)	4.828	0.091
No/Not sure	130 (51.8%)	121 (48.2%)		
Ever been encouraged by friends to try an AI Chatbot				
Yes	147 (60.7%)	95 (39.3%)	6.514	**0.014**
No	76 (47.8%)	83 (52.2%)		
Factors that discourage (or prevent) AI chatbot uptake for mental health *				
Fear that data/secrets will be leaked				
No	152 (57.1%)	114 (42.9%)	.751	0.397
Yes	71 (52.6%)	64 (47.4%)		
High cost of internet data subscription				
No	149 (55.8%)	118 (44.2%)	.012	0.916
Yes	74 (55.2%)	60 (44.8%)		
Do not know how to use these tools				
No	209 (55.4%)	168 (44.6%)	.077	0.835
Yes	14 (58.3%)	10 (41.7%)		
Prefer human connection/empathy over robots				
No	123 (57.7%)	90 (42.3%)	.839	0.367
Yes	100 (53.2%)	88 (46.8%)		
Religious beliefs against AI				
No	217 (55.5%)	174 (44.5%)	.080	0.100
Yes	6 (60.0%)	4 (40.0%)		
Unstable electricity/power to charge device				
No	157 (59.2%)	108 (40.8%)	4.181	**0.044**
Yes	66 (48.5%)	70 (51.5%)		
Factors that encourage AI chatbot uptake for mental health *				
24/7 Availability (especially late at night)				
No	97 (56.7%)	74 (43.3%)	.150	0.761
Yes	126 (54.8%)	104 (45.2%)		
Cheaper/Free compared to traditional therapy				
No	126 (51.2%)	120 (48.8%)	4.972	**0.030**
Yes	97 (62.6%)	58 (37.4%)		
Anonymity (nobody will know I have a problem)				
No	129 (54.9%)	106 (45.1%)	.118	0.760
Yes	94 (56.6%)	72 (43.4%)		
Instant response time				
No	114 (54.0%)	97 (46.0%)	.452	0.546
Yes	109 (57.4%)	81 (42.6%)		

** Multiple response item. α = 0.733*

With respect to having a family member who has suffered from mental health challenges, no statistically significant association was observed with level of uptake. Among those who confirmed a family member had been affected ($n = 113$), 64 (56.6%) recorded high uptake and 49 (43.4%) recorded low uptake, compared to 159 (55.2%) and 129 (44.8%), respectively, among those who reported no or were unsure of family exposure to mental health challenges ($n = 288$). The difference was not statistically significant (Fisher–Freeman–Halton exact $p = .256$).

With respect to having a friend or peer who uses AI tools for emotional support, those who reported a friend or peer with such engagement ($n = 150$) had a higher proportion recording high uptake ($n = 93$, 62.0%) compared to those who reported otherwise ($n = 251$, of whom 130, 51.8%, recorded high uptake). This association did not attain statistical significance (Fisher–Freeman–Halton exact $p = .091$).

With respect to being encouraged by friends to try an AI chatbot, those who had received such encouragement ($n = 242$) recorded a higher proportion of high uptake ($n = 147$, 60.7%) compared to those who had not been encouraged ($n = 159$, of whom 76, 47.8%, recorded high uptake). This association was statistically significant ($\chi^2 = 6.514$, $p = .014$).

With respect to being discouraged by fear that data or secrets would be leaked, no statistically significant association was found. Among those who cited this barrier ($n = 135$), 71 (52.6%) recorded high uptake, compared to 152 (57.1%) among those who did not ($n = 266$). The difference was not significant (Fisher's Exact $p = .397$).

With respect to being discouraged by the high cost of internet data subscription, those who endorsed this barrier (n = 134) and those who did not (n = 267) recorded comparable proportions of high uptake, 74 (55.2%) and 149 (55.8%), respectively. This association was not statistically significant (Fisher's Exact p = .916).

With respect to being discouraged by not knowing how to use AI tools, the proportion recording high uptake was 14 (58.3%) among those who cited this barrier (n = 24) and 209 (55.4%) among those who did not (n = 377). This difference was not statistically significant (Fisher's Exact p = .835).

With respect to being discouraged by a preference for human connection and empathy over robots, those who did not cite this barrier (n = 213) recorded a higher proportion of high uptake (n = 123, 57.7%) compared to those who did (n = 188, of whom 100, 53.2%, recorded high uptake). This difference was not statistically significant (Fisher's Exact p = .367).

With respect to being discouraged by religious beliefs against AI, the proportions of high uptake were similar across those who cited (n = 10; 60.0% high) and those who did not cite (n = 391; 55.5% high) this barrier. The association was not statistically significant (Fisher's Exact p = 0.100).

With respect to being discouraged by unstable electricity or difficulty charging devices, those who cited this barrier (n = 136) recorded a lower proportion of high uptake (n = 66, 48.5%) compared to those who did not (n = 265, of whom 157, 59.2%, recorded high uptake). This association was statistically significant ($\chi^2 = 4.181$, p = .044).

With respect to being encouraged by 24/7 availability, those who endorsed this facilitator (n = 230) and those who did not (n = 171) recorded similar proportions of high uptake, 126 (54.8%) and 97 (56.7%), respectively. This difference was not statistically significant (Fisher's Exact p = .761).

With respect to being encouraged by the fact that AI chatbots are cheaper or free compared to traditional therapy, those who endorsed this facilitator (n = 155) recorded a higher proportion of high uptake (n = 97, 62.6%) compared to those who did not (n = 246, of whom 126, 51.2%, recorded high uptake). This association was statistically significant ($\chi^2 = 4.972$, $p = .030$).

With respect to being encouraged by anonymity, those who endorsed this facilitator (n = 166) recorded 94 (56.6%) high uptake, compared to 129 (54.9%) among those who did not (n = 235). This association was not statistically significant (Fisher's Exact p = .760).

With respect to being encouraged by instant response time, those who endorsed this facilitator (n = 190) recorded 109 (57.4%) high uptake compared to 114 (54.0%) among those who did not (n = 211). The difference was not statistically significant (Fisher's Exact p = .546).

All other variables – including having a family member who has suffered from mental health challenges, being aware of a friend or peer who uses AI tools for emotional support, being discouraged by fear of data leakage, high cost of internet data subscription, not knowing how to use the tools, preference for human connection, religious beliefs against AI, 24/7 availability, anonymity, and instant response time – were not statistically significantly associated with level of uptake ($p > .05$).

Table 24: Predictors of uptake of AI chatbots.

Variables	B Regression Coefficient	Odds Ratio	95% CI for OR		p-value
			Lower	Upper	
Friend/peer who uses AI tools for emotional support					
Yes*		1			
No	-0.251	0.778	0.470	1.288	.330
Not sure	-0.597	0.551	0.327	0.925	**.024**
Ever been encouraged by friends to try an AI Chatbot					
No*		1			
Yes	0.481	1.618	1.051	2.492	**.029**
Factors that discourage (or prevent) AI chatbot uptake for mental health *					
Fear that data/secrets will be leaked					
No*		1			
Yes	-0.664	0.515	0.318	0.832	**.007**
High cost of internet data subscription					
No *	—	1	—	—	—
Yes	-0.111	0.895	0.560	1.430	0.644
Do not know how to use these tools					
No *	—	1	—	—	—
Yes	0.127	1.135	0.462	2.790	0.783
Prefer human connection/empathy over robots					
No*		1			
Yes	-0.495	0.610	0.383	0.971	**.037**
Unstable electricity/power to charge device					
No*		1			
Yes	-0.975	0.377	0.226	0.629	**< .001**
Factors that encourage AI chatbot uptake for mental health *					
Cheaper/Free compared to traditional therapy					
No*		1			
Yes	0.678	1.969	1.260	3.078	**.003**

*Reference category. $\alpha = 0.733$. Nagelkerke R^2 range: 0.102–0.115

Backward stepwise conditional logistic regression was conducted to identify predictors of high uptake of AI chatbots. The final model after eight elimination steps demonstrated adequate fit (Hosmer–Lemeshow $\chi^2 = 2.781$, df = 8, $p = 0.947$). The model explained 10.2% of the variance in uptake (Nagelkerke $R^2 = 0.102$) and correctly classified 63.1% of cases.

Six predictors were retained in the final model.

In relation to peer influence, respondents who were unsure whether a friend or peer used AI tools for emotional support had significantly lower odds of high uptake compared with those who were aware of peer AI engagement (OR = 0.551; 95% CI: 0.327–0.925; $p = 0.024$), indicating that uncertainty about peer behaviour predicted reduced uptake.

Respondents who had not been encouraged by friends to try AI chatbots were significantly less likely to exhibit high uptake compared with those who had received such encouragement (verify OR coding here, reported OR = 1.618; 95% CI: 1.051–2.492; $p = 0.029$), suggesting social encouragement was an important predictor of uptake.

Among discouraging factors, respondents citing fear of data or privacy breaches had significantly lower odds of high uptake (OR = 0.515; 95% CI: 0.318–0.832; $p = 0.007$). Similarly, respondents citing preference for human connection over robots had lower odds of high uptake (OR = 0.610; 95% CI: 0.383–0.971; $p = 0.037$).

Unstable electricity or difficulty charging devices emerged as the strongest negative predictor of uptake, with respondents citing this barrier having approximately 62% lower odds of high uptake compared with those who did not (OR = 0.377; 95% CI: 0.226–0.629; $p < 0.001$).

In relation to encouraging factors, respondents who cited the cost advantage of AI chatbots over traditional therapy had nearly twice the odds of high uptake compared with those who did not (OR = 1.969; 95% CI: 1.260–3.078; p = 0.003), indicating affordability as a significant positive predictor of uptake.

Variables not retained in the final model, including knowledge of how to use the tools, anonymity, cost of internet data subscription, religious beliefs against AI, 24-hour availability, family mental health history, and instant response time, were not significant predictors of uptake ($p > 0.05$).

Overall, peer influence, privacy concerns, infrastructural barriers, relational preferences, and affordability independently predicted respondents' level of AI chatbot uptake.

Table 25: Association between level of utilisation and factors influencing use of AI chatbots among Respondents

Variables	Level of Utilization		χ^2	p-Value
	High n (%)	Low n (%)		
Family member who has suffered from mental health challenges				
Yes	73 (64.6%)	40 (35.4%)	0.835	0.659
No	179 (62.2%)	109 (37.8%)		
Friend/peer who uses AI tools for emotional support				
Yes	109 (72.7%)	41 (27.3%)	13.192	**0.001**
No	143 (57.0%)	108 (43.0%)		
Ever been encouraged by friends to try an AI Chatbot				
Yes	167 (69.0%)	75 (31.0%)	9.935	**0.002**
No	85 (53.5%)	74 (46.5%)		
Factors that discourage (or prevent) AI chatbot utilization for mental health *				
Fear that data/secrets will be leaked				
Yes	102 (75.6%)	33 (24.4%)	14.085	**< 0.001**
No	150 (56.4%)	116 (43.6%)		
High cost of internet data subscription				
Yes	91 (67.9%)	43 (32.1%)	2.213	0.137
No	161 (60.3%)	106 (39.7%)		
Do not know how to use these tools				
Yes	20 (83.3%)	4 (16.7%)	4.590	**0.032**
No	232 (61.5%)	145 (38.5%)		
Prefer human connection/empathy over robots				
Yes	107 (56.9%)	81 (43.1%)	5.326	**0.021**
No	145 (68.1%)	68 (31.9%)		
Religious beliefs against AI				
Yes	7 (70.0%)	3 (30.0%)	0.225	0.635
No	245 (62.7%)	146 (37.3%)		
Unstable electricity/power to charge device				
Yes	86 (63.2%)	50 (36.8%)	0.014	0.907
No	166 (62.6%)	99 (37.4%)		
Factors that encourage AI chatbot utilization for mental health *				
24/7 Availability (especially late at night)				
Yes	156 (67.8%)	74 (32.2%)	5.736	**0.017**
No	96 (56.1%)	75 (43.9%)		
Cheaper/Free compared to traditional therapy				
Yes	111 (71.6%)	44 (28.4%)	8.322	**0.004**
No	141 (57.3%)	105 (42.7%)		
Anonymity/Privacy				
Yes	118 (71.1%)	48 (28.9%)	8.239	**0.004**
No	134 (57.0%)	101 (43.0%)		
Instant response time				
Yes	122 (64.2%)	68 (35.8%)	0.289	0.591
No	130 (61.6%)	81 (38.4%)		

* Multiple response item. α = 0.733

With respect to having a friend or peer who uses AI tools for emotional support, those who had such peers/friends had a higher proportion of respondents with high usage, 109 (72.7%), compared to those who did not, 62 (57.0%). This association was statistically significant ($\chi^2 = 13.192$, $p = 0.001$).

With respect to being encouraged by friends to try an AI Chatbot, those who were encouraged had a higher proportion of respondents with high usage, 167 (69.0%), compared to those who were not encouraged, 85 (53.5%). This association was statistically significant ($\chi^2 = 9.935$, $p = 0.002$).

With respect to being discouraged by the fear that data or secrets will be leaked, those who answered "Yes" had a higher proportion of respondents with high usage, 102 (75.6%), compared to those who answered "No", 150 (56.4%). This association was statistically significant ($\chi^2 = 14.085$, $p < 0.001$).

With respect to being discouraged by not knowing how to use these tools, those who answered "Yes" had a higher proportion of respondents with high usage, 20 (83.3%), compared to those who answered "No", 232 (61.5%). This association was statistically significant ($\chi^2 = 4.590$, $p = 0.032$).

With respect to being discouraged by a preference for human connection/empathy over robots, those who answered "No" had a higher proportion of respondents with high usage, 145 (68.1%), compared to those who answered "Yes", 107 (56.9%). This association was statistically significant ($\chi^2 = 5.326$, $p = 0.021$).

With respect to being encouraged by 24/7 availability (especially late at night), those who answered "Yes" had a higher proportion of respondents with high usage, 156 (67.8%), compared to those who answered "No", 96 (56.1%). This association was statistically significant ($\chi^2 = 5.736$, $p = 0.017$).

With respect to being encouraged by the fact that it is cheaper/free compared to traditional therapy, those who answered "Yes" had a higher proportion of respondents with high usage, 111 (71.6%), compared to those who answered "No", 141 (57.3%). This association was statistically significant ($\chi^2 = 8.322$, $p = 0.004$).

With respect to being encouraged by anonymity (nobody will know I have a problem), those who answered "Yes" had a higher proportion of respondents with high usage, 118 (71.1%), compared to those who answered "No", 134 (57.0%). This association was statistically significant ($\chi^2 = 8.239$, $p = 0.004$).

All other variables, including having a family member who has suffered from mental health challenges, being discouraged by the high cost of internet data subscription, being discouraged by religious beliefs against AI, being discouraged by unstable electricity/power to charge the device, and being encouraged by instant response time, were not statistically significantly associated with usage ($p > 0.05$).

Table 26: Predictors of utilization of AI chatbots

Variables	B Regression Coefficient	Odds Ratio	95% CI for OR		p-value
			Lower	Upper	
Friend/peer who uses AI tools for emotional support					
Yes*		1			
No	-0.312	0.732	0.431	1.244	0.249
Ever been encouraged by friends to try an AI Chatbot					
No*		1			
Yes	0.528	1.695	1.085	2.646	0.020
Factors that discourage (or prevent) AI chatbot utilization for mental health *					
Fear that data/secrets will be leaked					
No*		1			
Yes	0.658	1.931	1.182	3.154	0.009
High cost of internet data subscription					
No *	—	1	—	—	—
Yes	-0.265	0.768	0.406	1.452	0.416
Do not know how to use these tools					
No*		1			
Yes	1.130	3.095	0.984	9.739	0.053
Factors that encourage AI chatbot utilization for mental health *					
Cheaper/Free compared to traditional therapy					
No*		1			
Yes	0.399	1.490	0.938	2.367	0.091
24/7 Availability (especially late at night)					
No *	—	1	—	—	—
Yes	-0.154	0.858	0.469	1.567	0.618
Anonymity/Privacy					
No*		1			
Yes	0.516	1.675	1.058	2.653	0.028

*Reference category. α = 0.733. Nagelkerke R^2 range: 0.066–0.118

The backward stepwise logistic regression identified several significant predictors associated with the high utilization of AI chatbots among respondents. Peer influence played a substantial role as respondents who were "Not Sure" if their friends or peers used AI tools for emotional support had significantly lower odds of demonstrating high usage compared to those who definitively knew a peer who used them (OR = 0.405, 95% CI: 0.236–0.695, p = 0.001). Furthermore, receiving direct encouragement from friends to try an AI chatbot significantly increased a respondent's odds of high utilization by 69.5% (OR = 1.695, 95% CI: 1.085–2.646, p = 0.020).

Indicating "Fear that data/secrets will be leaked" as a discouraging factor was positively associated with usage; respondents who selected this concern were nearly twice as likely to exhibit high usage compared to those who did not (OR = 1.931, 95% CI: 1.182–3.154, p = 0.009), suggesting that frequent users may possess a heightened awareness of privacy risks. In terms of encouraging factors, "Anonymity (nobody will know I have a problem)" was a significant positive predictor, increasing the odds of high utilization by 67.5% (OR = 1.675, 95% CI: 1.058–2.653, p = 0.028). Note: Factors such as "Do not know how to use these tools" (p = 0.053) and finding it "Cheaper/Free compared to traditional therapy" (p = 0.091) were retained in the final stepwise iteration but fell just outside the conventional threshold for statistical significance ($p < 0.05$).

The following variables were omitted from the table because they were strictly non-significant and successfully removed during the stepwise elimination process (Steps 2 through 8): Family member suffered from mental health challenges, High cost of internet data subscription, Prefer human connection/empathy over robots, Religious beliefs against AI, Unstable electricity/power to charge device, 24/7 Availability, and Instant response time.

Table 27: Association between level of dependency and factors influencing use of AI chatbots among respondents.

Variables	Level of Dependency		χ^2	p-Value
	High n (%)	Low n (%)		
Family member who has suffered from mental health challenges				
Yes	25 (22.1%)	88 (77.9%)	5.604	.072
No/Not sure	37 (12.8%)	251 (87.2%)		
Friend/peer who uses AI tools for emotional support				
Yes	31 (20.7%)	119 (79.3%)	9.281	**.007**
No/Not sure	31 (12.4%)	220 (87.6%)		
Ever been encouraged by friends to try an AI Chatbot				
Yes	44 (18.2%)	198 (81.8%)	3.456	.068
No	18 (11.3%)	141 (88.7%)		
Factors that discourage (or prevent) AI chatbot dependency *				
Fear that data/secrets will be leaked				
No	40 (15.0%)	226 (85.0%)	.109	.771
Yes	22 (16.3%)	113 (83.7%)		
High cost of internet data subscription				
No	43 (16.1%)	224 (83.9%)	.253	.663
Yes	19 (14.2%)	115 (85.8%)		
Do not know how to use these tools				
No	57 (15.1%)	320 (84.9%)	.564	.395
Yes	5 (20.8%)	19 (79.2%)		
Prefer human connection/empathy over robots				
No	35 (16.4%)	178 (83.6%)	.327	.583
Yes	27 (14.4%)	161 (85.6%)		
Religious beliefs against AI				
No	59 (15.1%)	332 (84.9%)	1.658	.190
Yes	3 (30.0%)	7 (70.0%)		
Unstable electricity/power to charge device				
No	35 (13.2%)	230 (86.8%)	3.037	.108
Yes	27 (19.9%)	109 (80.1%)		
Factors that encourage AI chatbot dependency *				
24/7 Availability (especially late at night)				
No	26 (15.2%)	145 (84.8%)	.015	1.000
Yes	36 (15.7%)	194 (84.3%)		
Cheaper/Free compared to traditional therapy				
No	30 (12.2%)	216 (87.8%)	5.194	**.033**
Yes	32 (20.6%)	123 (79.4%)		
Anonymity (nobody will know I have a problem)				
No	31 (13.2%)	204 (86.8%)	2.238	.161
Yes	31 (18.7%)	135 (81.3%)		
Instant response time				
No	36 (17.1%)	175 (82.9%)	.872	.407
Yes	26 (13.7%)	164 (86.3%)		

* Multiple response item. $\alpha = 0.733$

With respect to having a family member who has suffered from mental health challenges, those who confirmed a family member had been affected ($n = 113$) recorded a higher proportion of high dependency ($n = 25$, 22.1%) compared to those who reported no or were unsure of family exposure to mental health challenges ($n = 288$, of whom 37, 12.8%, recorded high dependency). This difference did not attain statistical significance (Fisher–Freeman–Halton exact $p = .072$).

With respect to having a friend or peer who uses AI tools for emotional support, those who reported such a peer ($n = 150$) recorded a higher proportion of high dependency ($n = 31$, 20.7%) compared to those who did not or were unsure ($n = 251$, of whom 31, 12.4%, recorded high dependency). This association was statistically significant ($\chi^2 = 9.281$, $p = .007$).

With respect to being encouraged by friends to try an AI chatbot, those who had received such encouragement ($n = 242$) recorded a higher proportion of high dependency ($n = 44$, 18.2%) compared to those who had not ($n = 159$, of whom 18, 11.3%, recorded high dependency). This difference did not attain statistical significance (Fisher's Exact $p = .068$).

With respect to being discouraged by fear that data or secrets would be leaked, the proportions of high dependency were similar across those who cited this barrier ($n = 135$; 22, 16.3%) and those who did not ($n = 266$; 40, 15.0%). The association was not statistically significant (Fisher's Exact $p = .771$).

With respect to being discouraged by the high cost of internet data subscription, those who endorsed this barrier ($n = 134$) and those who did not ($n = 267$) recorded comparable proportions of high dependency, 19 (14.2%) and 43 (16.1%), respectively. The difference was not statistically significant (Fisher's Exact $p = .663$).

With respect to being discouraged by not knowing how to use AI tools, those who cited this barrier ($n = 24$) recorded 5 (20.8%) high dependency, compared to 57 (15.1%) among those who did not ($n = 377$). This association was not statistically significant (Fisher's Exact $p = .395$).

With respect to being discouraged by a preference for human connection and empathy over robots, those who cited this barrier ($n = 188$) recorded 27 (14.4%) high dependency, compared to 35 (16.4%) among those who did not ($n = 213$). The association was not statistically significant (Fisher's Exact $p = .583$).

With respect to being discouraged by religious beliefs against AI, those who cited this barrier ($n = 10$) recorded 3 (30.0%) high dependency, compared to 59 (15.1%) among those who did not ($n = 391$). Although the proportion was numerically higher, the association was not statistically significant (Fisher's Exact $p = .190$).

With respect to being discouraged by unstable electricity or difficulty charging devices, those who cited this barrier ($n = 136$) recorded a higher proportion of high dependency ($n = 27$, 19.9%) compared to those who did not ($n = 265$, of whom 35, 13.2%, recorded high dependency). This difference was not statistically significant (Fisher's Exact $p = .108$).

With respect to being encouraged by 24/7 availability, those who endorsed this facilitator ($n = 230$) and those who did not ($n = 171$) recorded virtually identical proportions of high dependency, 36 (15.7%) and 26 (15.2%), respectively. The association was not statistically significant (Fisher's Exact $p = 1.000$).

With respect to being encouraged by the fact that AI chatbots are cheaper or free compared to traditional therapy, those who endorsed this facilitator (n = 155) recorded a higher proportion of high dependency (n = 32, 20.6%) compared to those who did not (n = 246, of whom 30, 12.2%, recorded high dependency). This association was statistically significant ($\chi^2 = 5.194$, $p = .033$).

With respect to being encouraged by anonymity, those who endorsed this facilitator (n = 166) recorded 31 (18.7%) high dependency compared to 31 (13.2%) among those who did not (n = 235). This difference was not statistically significant (Fisher's Exact $p = .161$).

With respect to being encouraged by instant response time, those who endorsed this facilitator (n = 190) recorded 26 (13.7%) high dependency compared to 36 (17.1%) among those who did not (n = 211). This difference was not statistically significant (Fisher's Exact $p = .407$).

All other variables – including having a family member who has suffered from mental health challenges, being encouraged by friends to try an AI chatbot, being discouraged by fear of data leakage, high cost of internet data subscription, not knowing how to use the tools, preference for human connection, religious beliefs against AI, unstable electricity, 24/7 availability, anonymity, and instant response time – were not statistically significantly associated with level of dependency ($p > .05$).

Table 28: Predictors of dependency on AI chatbots.

Variables	B Regression Coefficient	Odds Ratio	95% CI for OR		p-value
			Lower	Upper	
Friend/peer who uses AI tools for emotional support					
Yes*		1			
No	-0.268	0.765	0.415	1.408	.389
Not sure	-1.201	0.301	0.137	0.663	**.003**
Ever been encouraged by friends to try an AI Chatbot					
No *	—	1	—	—	—
Yes	0.355	1.427	0.752	2.706	0.276
Fear that data/secrets will be leaked					
No *	—	1	—	—	—
Yes	-0.087	0.917	0.468	1.795	0.800
High cost of internet data subscription					
No *	—	1	—	—	—
Yes	-0.265	0.768	0.406	1.452	0.416
Factors that encourage AI chatbot dependency *					
Cheaper/Free compared to traditional therapy					
No*		1			
Yes	0.652	1.920	1.104	3.336	**.021**
Anonymity (nobody will know I have a problem)					
No *	—	1	—	—	—
Yes	0.542	1.720	0.924	3.201	0.087
Instant response time					
No *	—	1	—	—	—
Yes	-0.318	0.728	0.390	1.357	0.318
Family member who has suffered from mental health challenges					
Yes *	—	1	—	—	—
No	-0.507	0.602	0.308	1.177	0.138
Not sure	-0.701	0.496	0.232	1.061	0.071

*Reference category. α = 0.733. Nagelkerke R^2 range: 0.066–0.118

Backward stepwise conditional logistic regression was conducted with level of dependency (0 = Low, 1 = High) as the dependent variable, entering all Section F factors simultaneously at Step 1. The model underwent twelve elimination steps. The Hosmer–Lemeshow goodness-of-fit test at the final step indicated adequate model fit ($\chi^2 = 2.154$, df = 4, p = .707). The Nagelkerke R^2 for the final model was 0.066, and the overall correct classification rate was 84.5%.

Two predictors were retained in the final model. With regard to having a friend or peer who uses AI tools for emotional support, respondents who were not sure whether such a peer existed had significantly lower odds of high dependency compared to those who were certain of peer AI engagement for emotional support (OR = 0.301, 95% CI: 0.137–0.663, p = .003), indicating that direct awareness of peer AI use was associated with markedly increased odds of developing dependency. By contrast, respondents who reported no peer AI engagement did not differ significantly from those who knew of such peers (OR = 0.765, 95% CI: 0.415–1.408, p = .389).

With regard to encouraging factors, citing the cost advantage of AI chatbots over traditional therapy was associated with nearly double the odds of high dependency compared to those who did not endorse this facilitator (OR = 1.920, 95% CI: 1.104–3.336, p = .021). This finding suggests that the perceived affordability of AI chatbots may contribute not only to initial uptake and utilisation, but also to sustained and habitual reliance on such tools.

The following variables were removed during the stepwise elimination process and were not retained in the final model: prefer human connection/empathy over robots (Step 2), fear that data/secrets will be leaked (Step 3), do not know how to use the tools (Step 4), 24/7 availability (Step 5), high cost of internet data subscription (Step 6), being encouraged by friends to try an AI chatbot (Step 7), instant response time (Step 8), unstable electricity/power to charge device (Step

9), religious beliefs against AI (Step 10), family member who has suffered from mental health challenges (Step 11), and anonymity (Step 12).

CHAPTER FIVE

DISCUSSION OF FINDINGS

This chapter discusses the findings presented in Chapter Four of this study, which assessed knowledge, attitudes, and utilisation of artificial intelligence (AI) mental health chatbots among university students at the University of Benin (UNIBEN), Benin City, Nigeria. The discussion follows the sequence of the study objectives and is situated within relevant literature from Nigeria, Africa, and the international literature. Each section interprets the quantitative findings in relation to prior empirical evidence, identifies agreements and discrepancies with comparable studies, and addresses methodological or contextual factors that may account for observed differences. The chapter concludes with a summary of the principal findings.

The mean age of respondents was 21.84 years, which falls within the typical age range of undergraduate students in Nigerian public universities and is comparable with findings from similar studies conducted among university students in Nigeria and other low- and middle-income settings.[12,37] This age group represents late adolescence and early adulthood, a developmental period associated with increased vulnerability to common mental health disorders – such as depression, anxiety disorders, and stress-related conditions – and high engagement with digital technologies..

Male respondents constituted slightly over half of the study population. This distribution may reflect the enrolment structure of the institution, particularly the relatively higher representation of males in some science-based and professional programmes, and is similar to findings reported among Nigerian undergraduate populations.[38] Although gender differences in digital behaviour and help-seeking practices have been documented in the literature – with females generally reporting higher rates of emotional help-seeking and males demonstrating greater engagement with technology-based tools for non-therapeutic purposes – the distribution observed in this study provided adequate representation across both sexes, reducing the likelihood of gender-related sampling bias in the findings..

Students from medical faculties and departments comprised nearly two-thirds of the respondents while those from non-medical faculties comprised the remaining one-third. This distribution likely reflects the strong medical training presence within the institution and the proportionally larger student populations in the selected medical departments. The inclusion of both medical and non-medical students is important, as academic discipline may influence digital literacy, perceptions of artificial intelligence, and attitudes toward technology-assisted mental health support, with medical students potentially demonstrating greater awareness of clinically validated AI tools given their exposure to health informatics and evidence-based practice.

Respondents of Edo origin constituted slightly over half of the sample, while non-Edo respondents also represented a substantial proportion. This pattern reflects the institution's broad catchment characteristics and suggests reasonable sociocultural diversity among participants. The overwhelming majority of respondents were never married, which is expected in a predominantly young undergraduate population and is consistent with findings from comparable university-based studies.[31] In addition, students in the second and third years constituted the largest academic groups in the study population.

Overall, the sociodemographic profile of respondents provides important context for interpreting patterns of AI chatbot awareness, utilization, and mental health outcomes observed in this study.

Factors such as age, academic exposure, social environment, and disciplinary background may influence both receptivity to emerging technologies and vulnerability to psychological distress.

From a public health perspective, university students represent an important population for mental health research and intervention. This transitional stage of life is often associated with academic pressure, financial strain, evolving social roles, and increasing independence, all of which may contribute to psychological distress. Simultaneously, university students are highly digitally engaged, making them a potentially receptive population for technology-mediated mental health interventions, including AI chatbot–based support systems.

This study also found a high level of awareness of AI chatbots among respondents, with nearly all participants indicating familiarity with the concept. This high awareness may reflect the increasing integration of generative AI tools into digital platforms commonly used by young adults, including social media and messaging applications such as WhatsApp and Instagram. The finding appears higher than that reported among pharmacy students in a private Nigerian university,[31] but is consistent with evidence from a scoping review demonstrating generally high awareness of AI tools among higher education students globally.[39]

However, awareness was concentrated mainly around general-purpose AI platforms. While most respondents recognized widely used tools such as ChatGPT and Gemini, awareness of mental health–specific chatbots such as Woebot and Wysa was markedly low. Similar findings have been reported in other university-based studies, where familiarity with mainstream generative AI tools exceeded awareness of specialised digital mental health platforms.[40] This disparity likely reflects the greater visibility, accessibility, and widespread academic use of general-purpose AI tools compared with mental health–focused applications, particularly in low-resource settings.

Item-level findings further suggest that general awareness of AI does not necessarily translate into adequate knowledge of its mental health applications. Although overall knowledge levels appeared high, fewer respondents correctly identified functions such as anonymous emotional support, mood tracking, and emotion monitoring. This indicates important gaps in functional digital mental health literacy among students.

Ethnicity was not significantly associated with knowledge of AI chatbots in either the bivariate or multivariable analyses. Although Non-Edo indigenes demonstrated a slightly higher proportion of good knowledge compared with Edo indigenes, this difference did not attain statistical significance. Similarly, Non-Edo respondents had marginally higher odds of good knowledge in the adjusted model, although this finding also fell short of statistical significance. While the observed trend may suggest differences in prior digital exposure or access to technology, further investigation using larger and more ethnically diverse samples would be required to clarify this relationship.

Level of study demonstrated a significant association with knowledge, with odds of good knowledge increasing progressively across higher academic levels. Fourth-year students had over three times greater odds of good knowledge, while final-year students had nearly eight times greater odds relative to first-year students. This finding is consistent with previous Nigerian studies linking advanced academic level with greater AI knowledge.[31] The observed pattern may reflect cumulative exposure to digital tools through coursework, research activities, and professional or clinical training as students progress academically.

Conversely, older respondents demonstrated lower odds of good knowledge compared with the youngest age group. This pattern may reflect generational differences in familiarity and engagement with emerging digital technologies, with younger students potentially having greater exposure to AI-enabled platforms.

Conclusively, the above findings suggest that while general awareness of AI chatbots was high among university students, knowledge of their mental health–specific functions remain comparatively limited. This has important implications for digital mental health promotion within university settings. Interventions may therefore need to focus not only on awareness creation, but also on improving digital mental health literacy and promoting safe, informed, and appropriate use of AI chatbots for psychological support.

Furthermore, nearly three-quarters of respondents demonstrated positive attitudes towards the use of AI chatbots for mental health support. This finding contrasts with reports from some studies among university students in high-income settings, where attitudes toward chatbot-delivered support were more cautious when compared with traditional therapy.[9] However, this is consistent with findings from other settings, including studies among college students in the United States by Rackoff et al.,[9] medical students in China by Tao et al.,[23] and undergraduate students in the United Arab Emirates by Mosleh et al.,[22] where students expressed openness toward AI-assisted support because of convenience, accessibility, and perceived privacy.[41] The favourable attitudinal profile observed in this study may reflect the appeal of accessible digital support tools in contexts where formal mental health services are limited, underutilised, or affected by stigma.

At the item level, the highest agreement was recorded for the statement that AI chatbots can effectively educate students about mental health risks, endorsed by over three-fifths of respondents. This was followed closely by support for university policies promoting safe AI use and the need for caution among developers of AI mental health tools. Interestingly, nearly half of respondents disagreed that reliance on AI chatbots normalizes social isolation. Although previous studies in higher education settings have linked excessive AI use with reduced social interaction, the finding observed in this study may reflect the highly communal nature of university life within the study environment, where frequent interpersonal interactions remain common despite increasing digital engagement.[42]

A significant association was observed between knowledge and attitudes toward AI chatbots. Respondents with good knowledge had four times the odds of demonstrating positive attitudes compared with those with poor knowledge. This finding is consistent with evidence suggesting that understanding and perceived usefulness are important determinants of technology acceptance.[43] Greater familiarity with AI tools may therefore improve confidence and receptivity toward their mental health applications.

Religion was also significantly associated with attitude towards AI use, with Muslim respondents demonstrating higher odds of positive attitudes compared with Christian respondents. This finding may plausibly be related to a recent AI literacy and digital technology training programme organized for Muslim youths in Benin City shortly before data collection. Exposure to such programmes may improve awareness, familiarity, and confidence in the use of emerging digital technologies, thereby fostering more favourable attitudes toward AI chatbots.

Similarly, respondents who were ever married had significantly lower odds of positive attitudes compared with respondents who were never married. Age also demonstrated a significant inverse association with positive attitudes, with older respondents showing lower odds of favourable attitudes relative to the youngest participants. This may reflect generational differences in familiarity and comfort with emerging digital technologies.

Academic progression was significantly associated with attitudes, with students in higher academic levels demonstrating more favourable attitudes than those in lower levels. Final-year students had nearly eight times greater odds for positive attitudes relative to first-year students. This pattern may reflect increasing exposure to digital tools and greater appreciation of their practical utility over the course of university training. Similarly, the positive attitudes observed among Muslim respondents in this study may partly reflect this same trajectory, as greater familiarity with digital technologies acquired through years of academic engagement may foster a more favourable disposition toward AI-assisted mental health support, irrespective of religious affiliation. This suggests that longitudinal exposure to technology within the university environment may be a stronger determinant of positive AI attitudes than religious identity alone.

Overall, the positive attitudinal profile observed in this study suggests substantial acceptability of AI-supported mental health interventions among university students. From a public health perspective, this may provide an important opportunity for the introduction of appropriately regulated and evidence-based digital mental health interventions within university settings. However, the findings also highlight the need to ensure that increasing acceptance of AI tools is accompanied by adequate digital health literacy, institutional oversight, and appropriate safeguards to promote safe and responsible use.

In addition, this study found near-universal uptake of AI chatbots among respondents, with the vast majority reporting prior use. This level of adoption appears higher than reports from some university populations in the United States and China,[9,44] and likely reflects the increasing normalization of generative AI tools within students' academic and daily digital activities.

Multivariate analysis demonstrated that uptake was significantly associated with socioeconomic and environmental factors. Respondents from middle- and upper-socioeconomic classes had significantly higher odds of high uptake compared with those from lower socioeconomic backgrounds, while students residing off campus also demonstrated greater odds of uptake. These findings may be related to differences in access to enabling resources such as smartphones, stable internet connectivity, electricity, and greater autonomy in technology use.

The high uptake of AI chatbots observed in this study was further reflected in platform preference patterns, with ChatGPT emerging as the dominant AI tool. This is consistent with findings from other Nigerian studies reporting widespread use of generative AI platforms among university students.[31] Academic and school-related activities were also the most frequently reported reasons for AI chatbot use, supporting previous evidence that educational productivity remains a major driver of AI adoption among students.[39]

Despite this widespread general use, only a relatively small proportion of respondents reported using AI chatbots specifically for mental health support or emotional venting. Although this proportion compares favourably with some earlier reports,[9] it remains low relative to the high levels of general adoption and positive attitudes observed in this study. This suggests that while students are highly familiar with AI chatbots, awareness and utilization of their mental health–specific applications remain limited, particularly for specialized platforms such as Woebot and Wysa.

With respect to intensity of engagement, the most common pattern of use was occasional (“sometimes”) use, while indicators of high dependency were generally low. Most respondents reported minimal preoccupation with AI use and little perceived negative impact on academic performance or interpersonal relationships. This finding aligns with previous reports suggesting that although AI engagement is increasingly common among students, severe dependency remains comparatively infrequent.[44]

However, a minority of respondents demonstrated high dependency on AI chatbots, and religious affiliation emerged as a significant predictor of this pattern, with Muslim respondents demonstrating significantly higher odds of high dependency compared to their Christian counterparts. This association may reflect the greater social isolation and reduced access to culturally congruent peer support networks experienced by Muslim students as a religious minority within a predominantly Christian university environment. In this context, the anonymity and round-the-clock availability of AI chatbots may render them a particularly attractive substitute for human social connection, thereby increasing dependency risk among this subgroup.[39]

Academic level was also significantly associated with utilization, with students in intermediate and senior levels demonstrating substantially higher odds of high utilization compared with first-year students. This pattern may reflect increasing academic workload, research engagement, and integration of digital tools as students' progress through university training. Interestingly, this trend did not extend significantly to final-year students, possibly reflecting differences in academic structure or reduced applicability of generative AI tools during advanced clinical or professional training. Similar trends linking academic progression with increased AI engagement have been reported elsewhere.[45]

Religion was significantly associated with utilization, with Muslim respondents demonstrating higher odds of high utilization compared with Christian respondents. Similar to the attitudinal findings, this pattern may plausibly be related to the recent AI literacy and digital technology training programme organized for Muslim youths in Benin City prior to data collection. Exposure to such initiatives may improve familiarity, confidence, and engagement with AI technologies among participants.

Overall, the high uptake and utilization observed in this study suggest that AI platforms are already deeply integrated into students' daily routines. From a public health perspective, this presents an important opportunity for integrating evidence-based digital mental health interventions into platforms and communication channels already familiar to students. Rather than requiring adoption of entirely new systems, interventions may be more effective if embedded within existing patterns of digital engagement, while ensuring appropriate regulation, safety, and institutional oversight.

In addition, this study found that nearly three-fifths of respondents screened positive for depression, indicating a substantial burden of depressive symptoms within the study population. This prevalence may be attributable to several converging stressors characteristic of the Nigerian university environment, including intense academic pressure, financial hardship, inadequate access to formal mental health services, and the pervasive stigma surrounding help-seeking. Additionally, infrastructural challenges such as unstable electricity, poor internet connectivity, and uncertain post-graduation employment prospects may compound psychological distress among undergraduates, creating a chronic stress burden that predisposes this population to depressive symptoms. This prevalence appears higher than estimates reported in meta-analyses among Nigerian university students,[46] as well as findings from some institution-based Nigerian studies.[47] It also exceeds prevalence estimates reported among certain medical student populations and in broader African systematic reviews.[47,48] Variations across studies may reflect differences in study populations, prevailing socioeconomic and academic stressors, measurement tools, diagnostic thresholds, and timing of data collection.

At the symptom level, fatigue was the most frequently reported depressive symptom, followed by anhedonia and depressed mood, each reported by a substantial proportion of respondents. Of particular concern, passive suicidal ideation was reported at some frequency by nearly one-third of respondents. Given the clinical significance of suicidal thoughts, this finding represents an important public health concern within the university population. When considered alongside evidence of low help-seeking behaviour among students experiencing psychological distress,[12] the findings suggest that a considerable proportion of affected students may be suffering without accessing appropriate support services. These findings underscore the urgent need for the University of Benin to establish proactive, low-barrier mental health screening programmes and to integrate anonymous digital mental health support tools – including AI chatbots – into the university's student welfare framework, ensuring that vulnerable students have accessible pathways to early intervention before symptoms escalate to crisis level.

With respect to predictors of depression, age emerged as a significant factor, with respondents aged 18–24 years demonstrating significantly higher odds of depression compared with those aged below 18 years (OR = 3.759; 95% CI: 1.331–10.620). This finding is consistent with the well-established vulnerability of late adolescence and early adulthood to mood disorders, a period characterised by identity formation, academic transition pressures, and increasing social and financial independence, all of which may converge to heighten depressive risk within this age bracket.

Living arrangement was also significantly associated with depression, with off-campus residence demonstrating a protective effect relative to on-campus living. This may reflect differences in environmental stressors, overcrowding, privacy, sleep quality, and general living conditions commonly associated with hostel environments.

Although female respondents demonstrated a high proportion of depressive symptoms in the bivariate analysis, gender was not retained as an independent predictor in the multivariable model. This differs somewhat from much of the existing literature, where female students commonly demonstrate higher odds of depression and anxiety disorders.[49–51] The finding may suggest that within this study population, other contextual and environmental factors exerted stronger effects on depression risk after adjustment for potential confounders.

Students in medical departments demonstrated lower odds of depression compared with respondents in non-medical departments, although this association did not attain statistical significance. While this finding should be interpreted cautiously, it may reflect differences in academic structure, peer support systems, health literacy, or coping environments across disciplines.

Ethnicity was not significantly associated with depression, with relatively similar proportions observed across ethnic groups. This suggests that depressive burden within the study population may be driven more by shared university-related stressors than by ethnic background.

Importantly, patterns of AI engagement demonstrated differing relationships with depression. While higher general uptake of AI chatbots was associated with lower odds of depression, high utilization and high dependency were independently associated with increased odds of depressive symptoms. Respondents classified as high users had significantly higher odds of depression, while those with high dependency had more than twice the odds of screening positive for depression compared with respondents with low dependency. Similar associations between intensive digital engagement and adverse mental health outcomes have been reported in previous studies.[44,52] This suggests that while moderate engagement with AI tools may confer protective benefits through accessible emotional support, intensive and dependency-driven use may reflect or exacerbate underlying psychological distress rather than resolve it.

However, given the cross-sectional nature of this study, these associations should not be interpreted causally. It remains unclear whether intensive AI chatbot use contributes to psychological distress, whether psychologically distressed students are more likely to rely heavily on AI tools, or whether both phenomena reflect underlying vulnerabilities. Nonetheless, the findings suggest that the intensity and pattern of AI engagement, rather than AI use alone, may have important mental health implications.

Overall, the mental health profile identified in this study reveals a substantial burden of depressive symptoms among university students, alongside important associations involving age, living arrangement, and patterns of AI engagement. From a public health perspective, these findings underscore the urgent need for strengthened mental health screening programmes, improved access to student support services, and careful integration of safe, evidence-based digital mental health interventions within university settings.

Finally, in relation to additional factors influencing use of AI chatbots, this study identified peer influence, anonymity, affordability, privacy considerations, and infrastructural conditions as important determinants of AI chatbot use among respondents. While several factors appeared to facilitate engagement, concerns relating to empathy, data privacy, and digital access emerged as notable barriers to sustained utilization.

Peer influence appeared particularly important in shaping engagement with AI chatbots. Approximately three-fifths of respondents reported encouragement from friends to try AI chatbots, and this significantly increased the odds of both high uptake and high utilization. Similarly, respondents who were aware that their peers used AI tools for emotional support demonstrated significantly higher utilization, whereas uncertainty regarding peer behaviour was associated with reduced odds of high dependency. These findings reinforce the important role of peer networks in technology adoption among young adults. Similar observations have been reported among Nigerian students in digital health technology adoption studies[53] and among university students using generative AI tools in Tanzania.[45] Within university environments where behaviours and attitudes are often socially reinforced, peer influence may therefore serve as an important pathway through which AI chatbot engagement is initiated, normalized, and sustained.

Privacy-related concerns demonstrated a more complex relationship with AI chatbot use. Although fear of personal data leakage significantly reduced the likelihood of high uptake, privacy concerns were paradoxically associated with higher utilization. This finding may reflect the "privacy paradox" described in digital technology literature, whereby individuals continue to engage extensively with technologies despite awareness of potential privacy risks because perceived usefulness outweighs perceived harm.[54] In the present study, heavy users may therefore not necessarily have lacked concern regarding privacy, but rather may have considered the perceived benefits of AI engagement sufficiently valuable to justify continued use despite those concerns.

Anonymity and affordability also emerged as major facilitators of AI chatbot engagement. Respondents who perceived AI chatbots as anonymous and non-judgmental were significantly more likely to demonstrate high utilization. In addition, perceiving AI chatbots as a cheaper or free alternative to conventional therapy significantly predicted both high uptake and high dependency.[55] These findings are particularly relevant within settings where stigma, cost, shortage of mental health professionals, and limited access to formal mental healthcare continue to restrict help-seeking behaviour among students.[12] The attraction of anonymous digital support may therefore reflect not merely convenience, but also adaptation to structural and sociocultural barriers surrounding conventional mental healthcare services.

Structural accessibility factors further influenced engagement patterns. Twenty-four-hour availability and instant response time were among the most commonly reported facilitators, suggesting that convenience and immediacy substantially contribute to the appeal of AI chatbot platforms among students. However, relational concerns remained important barriers. Preference for human empathy over machine interaction emerged as the most frequently cited deterrent and significantly reduced the odds of high uptake. This finding is consistent with previous studies indicating that concerns regarding empathy, emotional understanding, trust, and contextual sensitivity continue to limit confidence in AI-mediated mental health support.[41,56] Although students may value accessibility and anonymity, many still appear to perceive human interaction as more emotionally authentic and therapeutically reassuring.

Importantly, infrastructural barriers remained substantial within the present study setting. Unstable electricity supply emerged as the strongest negative predictor of uptake, reducing the odds of high uptake by approximately 62%, while internet data costs were also frequently identified as barriers to utilization. These findings highlight the reality that engagement with digital mental health technologies is influenced not only by individual attitudes or perceived usefulness, but also by broader infrastructural and socioeconomic conditions. In many low-resource settings, inconsistent electricity supply, limited internet accessibility, and financial constraints may substantially hinder sustained engagement with digital health interventions, even where acceptance and willingness to use such technologies are high.

Taken together, these findings suggest that AI chatbot engagement among university students is shaped by a complex interaction of social influence, perceived utility, privacy considerations, relational preferences, and infrastructural realities. From a public health perspective, these findings imply that successful implementation of AI-enabled mental health interventions within university settings may require not only improved awareness and digital literacy, but also peer-supported dissemination strategies, strong privacy protections, affordable internet access, and infrastructural support systems capable of promoting equitable and sustained utilization.

Conclusion

This study identified high awareness and generally good knowledge of AI chatbots among university students, although awareness of clinically validated mental health–specific chatbots remained very limited. Academic progression and younger age were associated with better knowledge, suggesting that exposure to digital tools and generational familiarity shape understanding of AI technologies.

Attitudes toward AI mental health chatbots were largely positive, with good knowledge strongly associated with favourable attitudes. This suggests that understanding of AI functionality may influence openness to its mental health applications. However, the findings also indicate that positive attitudes coexist with important concerns regarding safety, regulation, and the boundaries of AI-delivered support.

AI chatbot uptake was near universal and primarily driven by academic use, while mental health–oriented use remained comparatively low. Utilization patterns were influenced by peer encouragement, anonymity, affordability, and privacy perceptions, whereas infrastructural limitations and preference for human empathy constrained engagement. These findings highlight that AI chatbot use in this population is shaped by social, technological, and contextual factors rather than by technological appeal alone.

A substantial proportion of respondents screened positive for depression, indicating considerable mental health burden within the study population. The observed associations between higher AI utilization, dependency, and depressive symptoms raise important questions regarding whether distressed students may be turning to AI as a coping mechanism, whether intensive reliance may relate to poorer wellbeing, or both. Although causality cannot be inferred from this cross-sectional study, these relationships warrant further longitudinal investigation.

Overall, the findings suggest that while university students demonstrate substantial digital readiness for AI-enabled interventions, safe integration of these tools into student mental health support will require more than technological availability. Digital mental health literacy, evidence-based regulation, institutional safeguards, and strengthened formal support systems are necessary to ensure that increasing AI engagement contributes to support rather than unintended harm.

Recommendations

1. To the Federal Ministry of Health / National Universities Commission (NUC)

1. Existing national digital health and mental health policy frameworks should be expanded to include specific regulatory guidelines for the use of artificial intelligence in psychological support services among young populations. Such frameworks should emphasize ethical deployment, clinical safety, user privacy, and data protection standards for AI-based mental health platforms used within tertiary institutions.
2. Ongoing collaborations between government agencies and telecommunication providers should be strengthened to improve affordable internet access for students using approved educational and mental health platforms. This may help reduce the infrastructural and financial barriers identified in this study, particularly internet data costs that limit sustained engagement with AI-supported mental health resources.
3. Existing digital literacy and General Studies (GST) programmes within Nigerian universities should be strengthened to include structured education on the safe, ethical, and appropriate use of AI technologies in health-related contexts. Particular attention should be given to clarifying the limitations of general-purpose AI chatbots in areas such as psychiatric diagnosis, medication prescription, and crisis management.
4. Government-supported innovation initiatives should encourage partnerships with local software developers, universities, and mental health professionals to improve the development of culturally relevant AI mental health tools adapted to the linguistic, social, and psychological realities of Nigerian students.

2. To the University of Benin (UNIBEN) Management / Student Affairs Division

1. Existing student counselling and wellness services within the University of Benin should be strengthened through the gradual integration of clinically validated AI-assisted mental health support tools as complementary – not replacement – resources for psychological support. This may improve accessibility for students who are reluctant to seek conventional face-to-face counselling.
2. Current counselling structures should incorporate anonymous and easily accessible digital support pathways capable of providing preliminary emotional support, psychoeducation, and referral guidance. Given that anonymity and round-the-clock accessibility emerged as important facilitators of use, a hybrid human-AI support model may enhance early engagement among vulnerable students.
3. Existing peer-support and student wellness initiatives should be expanded to include peer-led digital mental health awareness programmes. Since peer influence significantly predicted both uptake and utilization in this study, trained peer advocates may play an important role in promoting safe AI usage practices and reducing stigma associated with mental health help-seeking.
4. University health and counselling units should strengthen routine mental health screening and early identification strategies for students exhibiting signs of excessive or dependency-driven AI engagement. Given the observed association between high AI chatbot utilization and depressive symptoms, students presenting with problematic digital coping behaviours may benefit from timely psychological assessment and support.
5. Existing university ICT and digital infrastructure initiatives should be strengthened to improve stable internet access and electricity availability within learning environments, as

infrastructural limitations were identified as major barriers to sustained utilization of AI-based mental health resources.

3. To Individual Students / Undergraduates

1. Students should be encouraged to utilize AI chatbots primarily as supportive or supplementary tools for mental wellness, such as for stress management, psychoeducation, emotional reflection, and coping guidance, rather than as substitutes for professional psychiatric or psychological care.
2. Undergraduate students should strengthen personal digital safety practices by avoiding the disclosure of highly sensitive personal, emotional, or medical information on unverified digital platforms. Increased awareness of privacy and data protection issues may help address concerns regarding confidentiality and misuse of personal information.
3. Students should maintain balanced patterns of AI engagement and avoid excessive dependence on digital interactions as a means of escaping persistent emotional or social difficulties. Sustained human social support, peer interaction, and professional counselling remain important components of mental well-being.
4. Students experiencing persistent symptoms of depression, anxiety, emotional distress, or suicidal ideation should be encouraged to seek timely professional help through existing university counselling services, healthcare facilities, or qualified mental health professionals, even when utilizing AI-based support tools.

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APPENDIX I

INFORMED CONSENT FORM

TITLE OF STUDY: USE OF ARTIFICIAL INTELLIGENCE (AI) CHATBOTS IN INFLUENCING MENTAL HEALTH STATUS AMONG UNIVERSITY UNDERGRADUATES IN BENIN CITY, EDO STATE

INVESTIGATOR: HASSAN ABDULHAMEED OLUWASEYI

SUPERVISOR: Prof. Andrew I. OBI

FINANCIAL SPONSORSHIP: This research project is self-sponsored.

PURPOSE OF THE STUDY: The purpose of this study is to investigate the knowledge, attitudes, uptake, and level of utilization of Artificial Intelligence (AI) Chatbots for mental health support among undergraduate students in the University of Benin. Additionally, this study aims to assess the current mental health status of students and identify the factors influencing the adoption of these digital tools.

PROCEDURES INVOLVED IN THE STUDY:

You are requested to complete a structured, self-administered questionnaire designed to assess your socio-demographic characteristics, knowledge, attitudes, and patterns of AI chatbot usage. The questionnaire will also evaluate your current mental health status using a standardized screening scale and explore the factors (such as privacy concerns, data cost, and social influence) that facilitate or hinder the use of AI for mental well-being. The information collected will be used strictly for academic and research purposes.

COMPENSATION

There will be no financial compensation for participating in this study.

VOLUNTARY PARTICIPATION

Participation in this study is entirely voluntary. You are free to decline participation or withdraw at any time without any penalty, loss of benefits, or discrimination.

RISKS/SIDE EFFECTS

There are no anticipated risks or side effects associated with participating in this study.

BENEFITS

This study aims to generate evidence on the adoption and use of AI Chatbots for mental health support, which may inform future student wellness programs, institutional policies, and strategies for improving mental health service delivery on campus.

CONFIDENTIALITY

All information provided will be treated with strict confidentiality. Names or personal identifiers will not be collected. Data will be stored securely and used solely for research purposes.

CONSENT

By completing and submitting this questionnaire, you confirm that you have read and understood the information above and voluntarily agree to participate in this study.

CONTACT INFORMATION:

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Ethics and Research Committee

University of Benin Teaching Hospital Benin City

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CERTIFICATE OF CONSENT

I have read the above information (or it has been read to me). I had the opportunity to ask questions and the questions were answered to my satisfaction.

I voluntarily consent to take part in this study.

Signed_________________

APPENDIX II

QUESTIONNAIRE

USE OF ARTIFICIAL INTELLIGENCE (AI) CHATBOTS IN INFLUENCING MENTAL HEALTH STATUS AMONG UNIVERSITY UNDERGRADUATE STUDENTS IN BENIN CITY, EDO STATE

INSTRUCTION: Please tick (✓) the appropriate box or fill in the blank spaces where applicable. Your honest responses are appreciated and will be treated with strict confidentiality.

SECTION A: SOCIO-DEMOGRAPHIC CHARACTERISTICS

1. Age (at last birthday): ________ years
2. Gender: [ ] Male [ ] Female
3. Religion: [ ] Christianity [ ] Islam [ ] African Traditional Religion [ ] Others (specify): ____________
4. Ethnicity: [ ] Benin [ ] Yoruba [ ] Esan [ ] Igbo [ ] Hausa [ ] Others (specify): __________
5. Faculty: _________________
6. Department: ____________________
7. Level of Study: [ ] 100L [ ] 200L [ ] 300L [ ] 400L [ ] 500L [ ] 600L
8. Marital Status: [ ] Single [ ] Married [ ] Separated [ ] Divorced [ ] Cohabiting
9. Average Monthly Allowance/Income (in Naira): ____________________
10. Father’s Occupation: ______________
11. Father’s Level of Education: [ ] None [ ] Primary [ ] Secondary [ ] Tertiary
12. Mother’s Occupation: _________________
13. Mother’s Level of Education: [ ] None [ ] Primary [ ] Secondary [ ] Tertiary
14. Guardian’s Occupation: _____________
15. Guardian’s Level of Education: [ ] None [ ] Primary [ ] Secondary [ ] Tertiary
16. Current Living Arrangement: [ ] On-campus hostel [ ] Off-campus (alone) [ ] Off-campus (with family) [ ] Off-campus (with friends)

SECTION B: KNOWLEDGE OF AI CHATBOTS

Awareness and Sources of Information

17. Have you ever heard of the term "AI Chatbot"? [ ] Yes [ ] No
18. If yes, what was your source of information? (Tick all that apply) [ ] School/University lectures [ ] Social media posts/articles (Twitter, TikTok, etc.) [ ] Friends/Peers [ ] YouTube Videos [ ] Television/Radio [ ] Others (specify): ___________________
19. Which of the following AI tools have you heard of? (Tick all that apply) [ ] ChatGPT [ ] Gemini [ ] Meta AI (WhatsApp/Instagram) [ ] Snapchat MyAI [ ] Woebot (Mental health specific) [ ] Wysa (Mental health specific) [ ] None of the above
20. Which statement BEST defines an "AI Mental Health Chatbot"? (Choose ONE) [ ] A real human doctor chatting with you online. [ ] An automated software program that uses algorithms to mimic human conversation. [ ] A video call with a therapist. [ ] I don't know.
21. Are you aware that AI Chatbots can be used specifically to support mental health (therapy/counseling)? [ ] Yes [ ] No
22. In what ways can AI chatbots provide mental health support? (Tick all that apply) [ ] Providing coping tips and mindfulness exercises [ ] Tracking mood and emotional patterns [ ] Providing an anonymous platform to vent feelings [ ] Prescribing psychiatric medications
23. Do you understand that these AI chatbots are automated computer programs and not real humans? [ ] Yes [ ] No
24. Which daily timeframe of usage do you believe indicates a 'problematic dependency' on AI chatbots? [ ] Using it for less than 30 minutes daily [ ] Using it for 30 minutes to 1 hour daily [ ] Using it for more than 2 hours daily [ ] Checking it immediately after waking up

SECTION C: ATTITUDE TOWARDS AI CHATBOTS

Please indicate your level of agreement with the following statements. (A=Agree, N=Neutral, D=Disagree).

S/N	Statement	D	N	A
25.	AI chatbots can effectively influence a student's decision to seek help for mental health.			
26.	Content provided by AI chatbots for mental health support should be regulated by the University.			
27.	Developers and tech companies should be cautious about how AI interacts with students in distress.			
28.	Relying on AI chatbots for emotional support normalizes isolation from real people.			
29.	AI chatbots can be used effectively to educate students about mental health dangers.			
30.	I would report an AI chatbot if it gave harmful or dangerous advice.			
31.	University policies should promote the use of safe AI tools for student support.			
32.	I support regulations that limit the types of advice AI can give (e.g., no medical diagnosis).			
33.	Peer pressure plays a major role in whether I would use an AI chatbot.			
34.	Seeing friends post about using AI tools would influence my perception of them.			

35.	My religious beliefs discourage me from seeking emotional help from machines.			
36.	Religious leaders should speak more about the role of technology in mental well-being.			
37.	My cultural background influences my views about sharing secrets with a robot.			
38.	Cultural values regarding privacy make AI chatbots a better option than public counselling.			

SECTION D: LEVEL OF AI CHATBOT USE

DOMAIN 1: DIGITAL ACCESS & INVESTMENT

39. Do you own a mobile device? [ ] Yes [ ] No

40. What type of mobile device do you primarily use? (Tick all that apply) [ ] Smartphone [ ] Tablet [ ] Laptop [ ] Desktop Computer [ ] Others: _______

41. Do you have access to the internet? [ ] Yes [ ] No

42. What type of internet access do you have? [ ] Personal Mobile Data [ ] Institutional (School Wi-Fi) [ ] Cyber Café [ ] Others: ____________

43. If institutional is it embedded in school fees? [ ] Yes [ ] No

44. How much do you spend on data DAILY? (in Naira): ___________________

45. How much do you spend on data WEEKLY? (in Naira): ____________________

46. How much do you spend on data MONTHLY? (in Naira): ____________________

47. On average, how many hours do you spend online DAILY? ____________________ hours

48. On average, how many hours do you spend interacting with AI chatbots daily? [ ] 30 minutes [ ] 1 hour [ ] 2 hours [ ] > 2 hours [ ] I don't use them daily

DOMAIN 2: PATTERNS OF AI CHATBOT USE

49. Have you ever used an AI Chatbot (ChatGPT, Snapchat MyAI, etc.)? [ ] Yes [ ] No (If No, Skip to Section E)

50. How often do you use AI Chatbots? [ ] Very Rarely [ ] Rarely [ ] Sometimes [ ] Often [ ] Very Often

51. Which AI platform do you use most frequently? (Tick all that apply) [ ] ChatGPT [ ] Meta AI (WhatsApp/Instagram) [ ] Snapchat MyAI [ ] Gemini [ ] Woebot [ ] Wysa [ ] Others: _____

52. What do you use the AI for? (Tick all that apply) [ ] Academic/School Work [ ] Business/Work [ ] To Unwind/Relax [ ] Mental Health Support/Venting [ ] Others: ________

DOMAIN 3: INDICATORS OF PROBLEMATIC USE/DEPENDENCY

Thinking about your AI use over the LAST YEAR, please indicate how often the following has occurred:

1 = Very Rarely, 2 = Rarely, 3 = Sometimes, 4 = Often, 5 = Very Often

S/N	**Statement**	**1**	**2**	**3**	**4**	**5**
53.	You spent a lot of time thinking about the AI or planning when to use it next.					

54.	You felt an urge to use the AI more and more to feel satisfied.					
55.	You used the AI to forget about personal problems or avoid real-life stress.					
56.	You tried to cut down on using the AI without success.					
57.	You became restless or troubled if you were unable to access the AI.					
58.	You used the AI so much that it has had a negative impact on your studies or relationships.					

SECTION E: CURRENT MENTAL HEALTH STATUS

Over the last 2 weeks, how often have you been bothered by any of the following problems?

0 = Not at all, 1 = Several days, 2 = More than half the days, 3 = Nearly every day

S/N	**Question Item**	**Not at all**	**Several days**	**More than half the days**	**Nearly every day**
59.	Little interest or pleasure in doing things.				
60.	Feeling down, depressed, or hopeless.				
61.	Trouble falling or staying asleep, or sleeping too much.				
62.	Feeling tired or having little energy.				

63.	Poor appetite or overeating.				
64.	Feeling bad about yourself – or that you are a failure.				
65.	Trouble concentrating on things, (e.g., reading the newspaper or watching television).				
66.	Moving or speaking so slowly or being to fidgety/restless.				
67.	Thoughts that you would be better off dead or of hurting yourself in some way				

68. If you checked off any problems, how difficult have these problems made it for you to do your work? [ ] Not difficult at all [ ] Somewhat difficult [ ] Very difficult [ ] Extremely difficult

69. If you checked off any problems, how difficult have these problems made it for you to take care of things at home? [ ] Not difficult at all [ ] Somewhat difficult [ ] Very difficult [ ] Extremely difficult

70. If you checked off any problems, how difficult have these problems made it for you to get along with other people? [ ] Not difficult at all [ ] Somewhat difficult [ ] Very difficult [ ] Extremely difficult

SECTION F: FACTORS INFLUENCING USE

71. Is there any family member who has suffered from mental health challenges (e.g., depression, anxiety)? [ ] Yes [ ] No [ ] Not sure

72. Is there any friend/peer who uses AI tools for emotional support? [ ] Yes [ ] No [ ] Not sure

73. Have you ever been encouraged by friends to try an AI Chatbot? [ ] Yes [ ] No

74. Which of the following factors DISCOURAGES (or prevents) you from using AI for mental health? (Tick all that apply) [ ] High cost of internet data subscription [ ] Unstable electricity/power to charge my device [ ] Fear that my data/secrets will be leaked [ ] I prefer human connection/empathy over robots [ ] I do not know how to use these tools [ ] Religious beliefs against AI

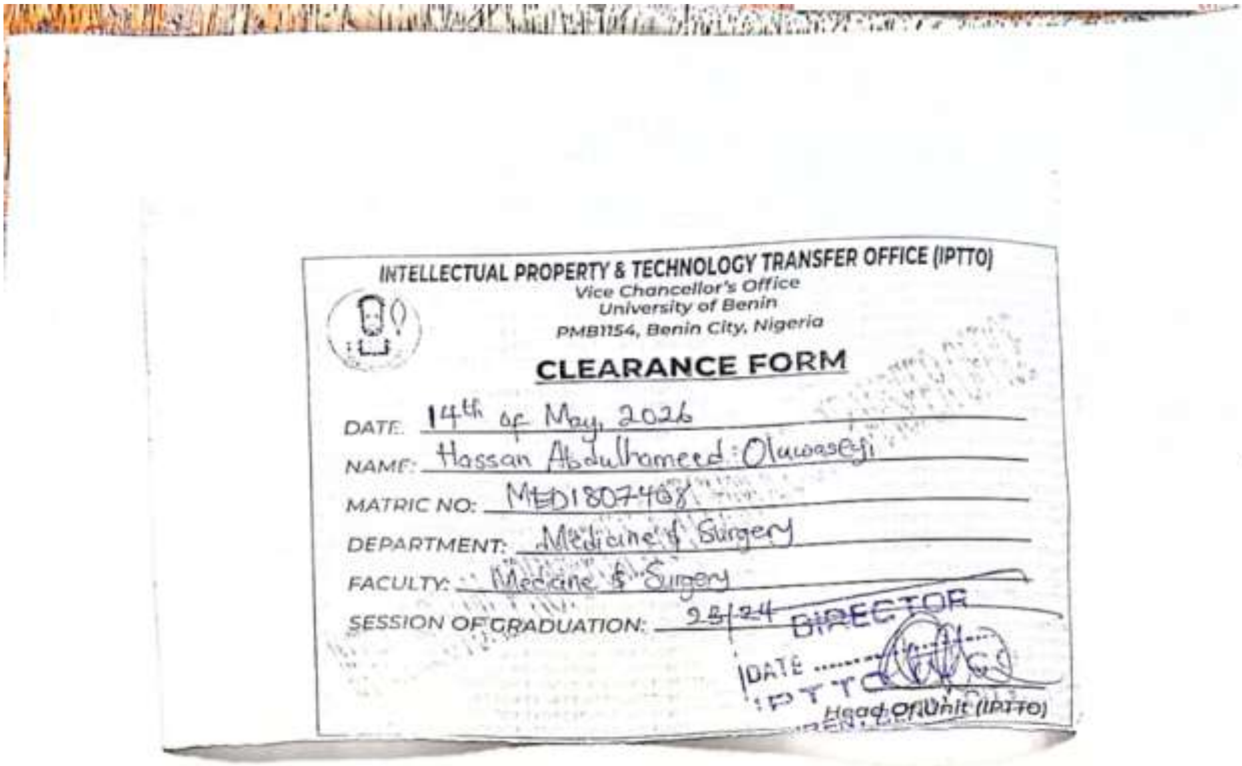
75. Which of the following factors ENCOURAGES (or would encourage) you to use AI? (Tick all that apply**)** [ ] 24/7 Availability (especially late at night) [ ] It is cheaper/free compared to traditional therapy [ ] Anonymity (Nobody will know I have a problem) [ ] Instant response time

76. What are the best ways the University can improve student mental health support?

____

THANK YOU FOR YOUR PARTICIPATION!

APPENDIX III



INTELLECTUAL PROPERTY & TECHNOLOGY TRANSFER OFFICE (IPTTO)
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CLEARANCE FORM

DATE: 14th of May, 2026

NAME: Hassan Abdulhameed Oluwaseyi

MATRIC NO: MED1807408

DEPARTMENT: Medicine & Surgery

FACULTY: Medicine & Surgery

SESSION OF GRADUATION: 23/24

DIRECTOR

DATE ....

IPTTO

Head of Unit (IPTTO)