USE OF ARTIFICIAL INTELLIGENCE CHATBOT IN FACILITATING SELF-MEDICATION PRACTICES AMONG UNDERGRADUATE STUDENTS IN BENIN CITY, EDO STATE.

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ONE YEAR PROJECT PRESENTED TO THE DEPARTMENT OF PUBLIC HEALTH AND COMMUNITY MEDICINE, UNIVERSITY OF BENIN, BENIN CITY, EDO STATE, NIGERIA IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF BACHELOR OF MEDICINE AND BACHELOR OF SURGERY (MBBS) DEGREE IN THE UNIVERSITY OF BENIN

MAY, 2026.

DECLARATION

I hereby declare that this research project titled **"USE OF ARTIFICIAL INTELLIGENCE CHATBOT IN FACILITATING SELF-MEDICATION PRACTICES AMONG UNDERGRADUATE STUDENTS IN BENIN CITY."** was carried out by **EKANEM GRACE NSEABASI** with matriculation number **MED1807393** under supervision of Professor A. I. Obi and has not been submitted anywhere else in part or in full for the award of a degree or certificate.

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CERTIFICATION

This is to certify that this research study titled **"USE OF ARTIFICIAL INTELLIGENCE CHATBOT IN FACILITATING SELF-MEDICATION PRACTICES AMONG UNDERGRADUATE STUDENTS IN BENIN CITY."** was conducted by **EKANEM GRACE NSEABASI** with matriculation number **MED1807393** 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 to God Almighty, the source of my strength and wisdom throughout this journey. To my parents and siblings, I am deeply grateful for your love, support, and encouragement. I also dedicate this work to the patient I met during my mental health posting, whose experience inspired this study and deepened my commitment to compassionate care.

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Ekanem Grace Nseabasi

TABLE OF CONTENTS

CHAPTER THREE

CHAPTER FOUR

CHAPTER FIVE

LIST OF ABBREVIATION

AI	Artificial Intelligence
AD	Alzheimer’s Disease
ADHD	Attention Deficit Hyperactivity Disorder
AGI	Artificial General Intelligence
AR	Augmented Reality
CT	Computed Tomography
DDI	Drug–Drug Interaction
EGD	Esophagogastroduodenoscopy
EHR	Electronic Health Records
FDA	Food and Drug Administration
HBM	Health Belief Model
MBBS	Bachelor of Medicine, Bachelor of Surgery
MRI	Magnetic Resonance Imaging
NLP	Natural Language Processing
PTSD	Post-Traumatic Stress Disorder
SMH	Self-Medication Hypothesis
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
VR	Virtual Reality
WHO	World Health Organization

OPERATIONAL DEFINITION OF TERMS

AI Chatbot: A computer program that uses artificial intelligence techniques, particularly natural language processing, to simulate human conversation and provide automated responses to user inputs.

Artificial Intelligence (AI): A branch of computer science concerned with the development of systems capable of performing tasks that typically require human intelligence, including learning, reasoning, problem-solving, and decision-making.

Digital Health: The application of digital technologies, such as mobile devices, software, and artificial intelligence, to support healthcare delivery, health education, and health system management.

Health Belief Model (HBM): A psychological model that explains and predicts health behaviors based on individuals' perceptions of susceptibility, severity, benefits, barriers, cues to action, and self-efficacy.

Health-seeking Behaviour: Any action undertaken by an individual who perceives a health problem for the purpose of finding an appropriate remedy or healthcare solution.

Self-medication: The selection and use of medicines by individuals to treat self-recognized illnesses or symptoms without professional medical advice or prescription.

Technology Acceptance Model (TAM): A theoretical model that explains how users come to accept and use a technology, primarily based on perceived usefulness and perceived ease of use.

Undergraduate Students: Individuals enrolled in a university or higher education institution who are pursuing their first academic degree.

ABSTRACT

Background: Artificial intelligence (AI) chatbots are increasingly being used as source of health information, particularly among undergraduate students who are highly engaged with digital technologies. These tools provide instant, interactive, and personalized responses to health-related queries, which may influence health-seeking behaviors. One growing concern is their role in facilitating self-medication, defined as the use of medicines without consultation with qualified healthcare professionals. While AI chatbots may improve access to health information and empower individuals to make decisions, their unregulated use raises concerns about misinformation, inappropriate drug use, delayed diagnosis, and adverse health outcomes. Despite the increasing global use of AI technologies, there is limited evidence on how undergraduate students in Nigeria utilize AI chatbots in relation to self-medication practices. Understanding students' knowledge, attitudes, and patterns of use is essential for informing public health interventions and policies.

Methods: An analytical cross-sectional study was conducted among undergraduate students in Benin City, Nigeria. Data were collected using a structured, self-administered questionnaire adapted from UTAUT and related acceptance models that assessed socio-demographic characteristics, knowledge of AI chatbots, attitudes toward their use in health decision-making, and prevalence of their use in facilitating self-medication. Knowledge and attitude scores were computed and categorized into levels. Data analysis was performed using appropriate statistical software. Descriptive statistics such as frequencies and proportions were used to summarize variables, while inferential statistics, including chi-square tests, were used to examine associations between variables. Statistical significance was set at $p < 0.05$.

Results: The mean age of respondents was 21.50±3.138 years, with females constituting the majority (78.4%). Awareness of AI chatbots was universal, and about four-fifth of respondents demonstrated good knowledge, with Gemini being the most correctly identified tool. Despite this high awareness, only a small proportion had received formal training on AI or chatbots. About seven-tenth of respondents expressed a positive attitude toward AI chatbot use, perceiving these tools as convenient and useful for obtaining quick health information, although concerns regarding reliability and safety remained common. The prevalence of AI chatbot use for self-medication was considerable, with nearly one-third of respondents reporting use for advice on symptoms, possible diagnoses, and treatment options. ChatGPT was the most commonly used chatbot for self-medication, followed by Gemini. Despite the prevalence of use, the frequency of chatbot utilization for self-medication was mostly occasional or rare. Sex and guardians occupation were significant predictors of good knowledge. Attitude toward AI chatbot use was a strong predictor of prevalence. Respondents with a positive attitude were significantly less likely to use AI chatbots for self-medication compared with those with a negative attitude (OR = 0.178, $p < 0.001$)

Conclusion: Despite high awareness and good knowledge of AI chatbots among respondents, concerns about reliability and safety in self-medication persisted. About one-third had used AI chatbots, mainly ChatGPT, for self-medication. Knowledge, attitude, guardians' occupation, and social media use significantly influenced utilization, highlighting the need for targeted health education, improved digital health literacy, and regulatory frameworks to ensure safe and responsible use of AI chatbots in healthcare decision-making.

Keywords: Artificial intelligence, chatbots, self-medication, undergraduate students, digital health, Nigeria

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CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Artificial intelligence is often defined as the capacity of computer-driven systems to extract information, learn from it, and utilize the acquired knowledge to complete certain tasks to some degree of autonomy.[1] In recent years, the range of applications of artificial intelligence technologies has grown significantly beyond technical disciplines, and has penetrated real-life process affecting how individuals work, learn and make decisions.[2] The AI chatbot is one of the most common and the most apparent types of artificial intelligence currently, as it provides people with the means to connect to software systems by means of natural language dialogues. Such chatbots are now integrated in the search engines, mobile apps, and social media networks, thus they can be easily accessed by the youths, and even university students.[3]

Artificial intelligence has become widely used in healthcare in the support of clinical decision-making, diagnostics, and health information provision.[4] Some of the medical imaging interpretation, predicting the risk of diseases, drug development, and patient monitoring are some of the areas where AI-based systems have demonstrated to be useful.[5] Outside the formal healthcare environment, AI chatbots are becoming a popular choice among general public to find information about their health, such as an explanation of symptoms, potential diagnosis, and prescriptions of the possible treatments.[6] This change has transformed the manner in which people obtain health-related information whereby they no longer rely on the conventional sources of health information providers like the healthcare professionals, but rather turn towards digital and automated delivery methods.

Self-medication is the use of medicines or treatment methods without consulting a physician, and often based on personal opinion or recommendation by non-medical individuals.[7] Self-medication is also common among the university students because of various factors, including academic stress, lack of time, the subjective perception of mildness of symptoms, previous experience of medications, and the ease of access to drugs.[8] Prescription laws in most low and middle-income nations, such as Nigeria, tend to be weakly enforced and students are able to get drugs without sound medical advice.[9] It is a practice that raises the likelihood of inappropriate medicine use, adverse medication reactions, antimicrobial resistance, and a late diagnosis of severe illnesses.

Self-medication practices are getting a new dimension with the ever-increasing availability of AI chatbots. Compared to the conventional internet searches, AI chatbots answer questions in an interactive, personalized, and authoritative way, which can affect the perception of the user making a self-diagnosis and treatment choice.[10] Undergraduate students who typically are digitally literate, and use technology frequently are more susceptible to use the tools to obtain fast health advice.[11] Although AI chatbots have potential benefits when it comes to access to health information, self-medication should be viewed as a question of accuracy, information misinterpretation, and a deficit in context-specific guidance.[12]

Knowledge plays a critical role in how individuals interact with AI chatbots for health purposes. Knowledge that is sufficient should comprise the awareness of what AI chatbots are, how they operate, their shortcomings and the dangers of using them to make medical choices.[12,13] In the absence of this knowledge, students can unrealistically trust the advice provided by chatbots and cannot identify the cases when medical assistance is needed. Attitudes toward AI chatbots also shape usage patterns. Positive attitudes can lead to the frequent use and trust in chatbot responses, whereas negative or skeptical attitudes can hinder the use of such tools.[14]

Globally, concerns about the safety, ethics, and regulation of artificial intelligence (AI) in healthcare have led to the development of several policy frameworks to guide its responsible use. The World Health Organization in 2021 released the "Ethics and Governance of Artificial Intelligence for Health" guideline, which emphasized that AI tools used in healthcare must ensure transparency, accountability, patient safety, privacy, and human oversight. The guideline warned against overreliance on AI-generated medical advice and stressed the need for regulatory systems to protect users from misinformation and unsafe self-medication practices. Similarly, UNESCO adopted the "Recommendation on the Ethics of Artificial Intelligence" in 2021, encouraging member states to establish legal and ethical safeguards for AI applications, especially in health-related settings, to prevent harm and promote responsible use.[15]

In Nigeria, regulation of AI use in healthcare and self-medication is still evolving, although several national digital health and data governance policies provide a foundation for control. The Federal Ministry of Health's National Digital Health Strategic Framework promotes the safe integration of digital technologies into healthcare delivery, while the Nigeria Data Protection Act and the Nigeria Data Protection Regulation (NDPR) emphasize confidentiality, privacy, and responsible handling of users' health information. In addition, agencies such as the National Agency for Food and Drug Administration and Control and the Medical and Dental Council of Nigeria regulate medication use and medical practice, which indirectly applies to AI-generated medical advice and self-medication practices. However, Nigeria currently lacks a comprehensive AI-specific healthcare regulation, highlighting the need for policies that specifically address the use of AI chatbots in health information seeking and self-medication among young people and students..[15] Students with limited health literacy might rely on chatbot advice more, whereas higher-technology confident students might avoid the old systems of healthcare. At the same time, the perception and utilization of AI tools in health decisions among students can be influenced by cultural beliefs, peer influence, and prior experiences with the healthcare systems.

1.2 Statement of the Problem

A wide practice among undergraduate students is self-medication which has been linked to grave health implications such as wrong prescription of drugs, side effects as well as late medical treatment.[6] This is due to the growing access to artificial intelligence chatbots, which is becoming a new and, to a great extent, unregulated source of health information.[10] Quick and persuasive answers to health-related queries can be delivered by AI chatbots and this can lead to students making medical decisions without involving qualified healthcare professionals.[12]

Self-medication remains a major public health issue globally and particularly in Nigeria. Self-medication refers to the use of medicines by individuals to treat self-recognized symptoms or illnesses without professional medical consultation. Although responsible self-medication may provide certain benefits such as convenience and reduced healthcare costs, inappropriate self-medication has been associated with adverse drug reactions, drug dependence, antimicrobial resistance, masking of serious illnesses, delayed diagnosis, and increased morbidity and mortality. In Nigeria, the high prevalence of self-medication has been linked to factors such as long waiting times in health facilities, poor access to healthcare services, financial limitations, easy access to over-the-counter medications, and reliance on informal sources of health information. A national community-based survey in Nigeria reported a self-medication prevalence of 69.4%, with headaches, malaria, cough, upper respiratory tract infections, and body pains being the most common conditions for which self-medication was practiced. Convenience, time-saving, long hospital queues, and financial constraints were major reasons for the practice.[13] With the emergence of AI chatbots capable of generating medical and drug-related information, there is growing concern that these technologies may further encourage self-medication behaviors, particularly among young adults and students who frequently use digital tools for information seeking.

Several international studies have demonstrated increasing awareness and utilization of AI chatbots among undergraduate students, especially those in health-related disciplines. A global study conducted among healthcare students in the Americas reported that although respondents had relatively low self-reported knowledge of ChatGPT, many participants perceived the technology as useful for healthcare practice, obtaining reliable information, and simplifying academic and clinical work. Approximately 70% of respondents reported using ChatGPT for educational activities, and positive perceptions of the technology were strongly associated with favorable attitudes toward its use in healthcare settings.[14] Similarly, a South African study among undergraduate students found that students preferred AI-powered healthcare assistants that provided confidentiality, local language support, personalized advice, and context-specific healthcare information.[15] These findings suggest that contextual relevance, accessibility, and trust significantly influence the acceptance and utilization of AI chatbots among university students.

Studies from Asia, the Middle East, and Africa have further highlighted the growing role of AI chatbots in health-related information seeking and decision-making among students. In China, social influence, perceived trust, enabling conditions, and behavioral intentions significantly predicted chatbot adoption among medical students.[16] Similarly, research conducted among healthcare students in Malaysia found that higher knowledge levels and positive attitudes toward AI were associated with increased use of AI chatbots. [17] In Arab countries, a multinational study involving over 12,000 participants found that awareness of AI chatbots was high, although only about one-quarter had used them in healthcare contexts. Chatbots were commonly used for self-diagnosis, self-medication, health coaching, and mental health support, while concerns regarding reliability and accuracy persisted among users. [18] These findings demonstrate that AI chatbots are increasingly influencing health-seeking behavior among young adults globally.

In Nigeria, awareness and use of AI chatbots among undergraduate students have also increased rapidly in recent years. Several studies conducted among medical, pharmacy, and allied health students have demonstrated high levels of familiarity with AI chatbots, especially ChatGPT. A study conducted among pharmacy students at Afe Babalola University revealed that most students were familiar with AI chatbots and frequently used them for academic purposes such as assignments and studying. [19] Although respondents generally believed that AI tools improved academic performance, concerns regarding academic dishonesty, misinformation, distraction, and ethical issues were also identified. [19] Another Nigerian study conducted among medical and allied health students reported that most respondents possessed moderate-to-good knowledge of ChatGPT and frequently used it because of its convenience and efficiency. [20] However, significant concerns regarding inaccuracy, dependence, reliability, and ethical implications were reported. [20] Similar findings were reported in studies conducted at Ekiti State University and Abia State University, where students generally demonstrated positive attitudes toward AI chatbots but remained cautious about their reliability in healthcare decision-making. [21, 22]

Despite increasing awareness and acceptance of AI chatbots among Nigerian undergraduate students, formal education and training on the safe and responsible use of these technologies remain limited. Several studies have shown that only a small proportion of students had received structured training on AI tools despite widespread usage. [19, 22] Consequently, many students rely on self-directed learning and social media exposure to interact with AI chatbots, which may increase the likelihood of misinformation and unsafe use. Evidence also suggests that socio-demographic and academic factors such as age, sex, academic level, prior AI exposure, social influence, guardians' occupation, and perceived usefulness significantly influence students' attitudes toward and use of AI chatbots. [23, 24, 25, 17, 16, 26, 27] These factors may also shape how students use AI-generated information for health-related purposes, including self-medication.

The growing use of AI chatbots in health information seeking presents important public health concerns because AI-generated responses may not always be accurate, evidence-based, or contextually appropriate. AI chatbots can sometimes provide misleading or incomplete medical information, fail to recognize medical emergencies, or generate inappropriate medication recommendations. Undergraduate students, particularly those with limited health literacy or inadequate clinical knowledge, may be vulnerable to relying on such information without consulting qualified healthcare professionals. This could increase the risk of inappropriate drug use, adverse drug reactions, delayed healthcare seeking, antibiotic misuse, and poor health outcomes. Furthermore, the increasing dependence on AI-generated health advice may contribute to reduced professional consultation and reinforce unsafe self-medication practices among students.

Although previous studies in Nigeria have explored awareness, perceptions, attitudes, and academic use of AI chatbots, there remains limited empirical evidence specifically examining the use of AI chatbots in facilitating self-medication practices among undergraduate students. Most available Nigerian studies have focused primarily on educational applications of AI tools rather than their implications for healthcare behavior and medication practices. [19, 21, 20, 22] In addition, there is limited information regarding the prevalence of AI chatbot use for self-medication, the extent of students' knowledge regarding AI-generated health information, and the socio-demographic and academic factors influencing such practices among undergraduate students. This lack of evidence creates an important research gap, particularly in the context of increasing AI adoption and the high burden of self-medication practices in Nigeria.

Given the rapid expansion of AI technologies and the potential risks associated with inappropriate self-medication, there is a need to generate evidence on how undergraduate students utilize AI chatbots for health-related decision-making. Understanding students' knowledge, attitudes, prevalence of use, and associated factors is important for informing public health interventions, digital health literacy programmes, university policies, and regulatory frameworks aimed at promoting the safe and responsible use of AI technologies in healthcare. Therefore, this study seeks to assess the knowledge, attitudes, prevalence, and factors associated with the use of AI chatbots for self-medication practices among undergraduate students.

Another important concern is the absence of comprehensive national policies and regulatory frameworks guiding the use of artificial intelligence chatbots in healthcare and health information dissemination in Nigeria. Although AI technologies are increasingly being adopted, Nigeria currently lacks a dedicated AI law or comprehensive AI-specific regulatory framework governing the deployment and use of AI systems, including healthcare chatbots. Existing governance mainly relies on general data protection and digital technology regulations rather than specific AI legislation.[28,29] This regulatory gap may contribute to misinformation, inappropriate medication recommendations, misuse of health information, and reduced professional oversight. Furthermore, there are limited institutional guidelines within Nigerian universities regarding the responsible use of AI chatbots for healthcare decision-making, which may increase the risk of unsafe self-medication practices among undergraduate students.

1.3 Justification of Study

The increasing use of artificial intelligence chatbots for health information has influenced health-seeking behaviors among undergraduate students, who frequently rely on digital platforms for quick health-related answers.[1,2] At the same time, self-medication remains common among students, especially in low- and middle-income countries where access to healthcare services may be limited.[3] The relationship between AI chatbot use and self-medication therefore represents an emerging public health concern that requires further investigation.

Understanding students' knowledge of AI chatbots is important because limited or incorrect knowledge may lead to misuse of these tools and inappropriate health decisions.[4] Assessing attitudes is equally important, as positive perceptions and high trust in chatbot responses may increase reliance on non-professional advice for medication use.[5] Determining the prevalence of AI chatbot use in facilitating self-medication will help to establish the extent of this practice among undergraduates in Benin City.[6] Without such data, the scale of potential risks, such as drug misuse and delayed medical consultation, remains unclear.[7]

This study is justified by the lack of local evidence on AI chatbot use for self-medication among undergraduate students in Nigeria. Most existing research focuses on clinical applications of AI or on populations in high-income countries, which limits applicability to the local context. Findings from this study will provide baseline data that can inform health education programs, guide university health services, and support the development of policies on digital health literacy and responsible use of AI tools.

1.4 Research Questions

The following questions guided this study

1. What level of knowledge does undergraduate students in Benin City have about artificial intelligence chatbots used for health-related purposes?
2. What are the attitudes of undergraduate students toward the use of AI chatbots in making self-medication decisions?
3. What is the prevalence and level of utilization of use of AI chatbots in facilitating self-medication practices among undergraduate students in Benin City?
4. What are factors influencing use and level of utilization of AI chatbots for self-medication among undergraduate students?

1.5 Objective of the Study

Aim: To assess the use of artificial intelligence chatbots in facilitating self-medication practices among undergraduate students in Benin City in order to inform interventions aimed at promoting the safe use of digital health tools and reducing inappropriate self-medication among students.

Specific Objectives

1. To assess the level of knowledge of undergraduate students regarding artificial intelligence chatbots used for health information and advice.
2. To ascertain attitudes of undergraduate students toward the use of AI chatbots for self-medication practices.
3. To determine the prevalence and level of utilization of use of artificial intelligence chatbots in facilitating self-medication among undergraduate students in Benin City.
4. To identify factors influencing use and level of utilization of AI chatbots for self-medication among undergraduate students.

CHAPTER TWO

LITERATURE REVIEW

2.1 Background of Artificial Intelligence in Healthcare

Artificial intelligence (AI) refers to computer systems that can perform tasks requiring human intelligence such as learning, reasoning, problem-solving, perception, and decision-making.[28] AI is a branch of computer science that enables machines to perceive their environment, learn from data, and make decisions to achieve set goals.[29] Common AI applications include search engines, recommendation systems, virtual assistants, autonomous vehicles, and content-generation tools.[30] AI has evolved significantly since its emergence in 1956, especially after advances in deep learning, GPUs, and transformer models, which accelerated the growth of generative AI technologies in the 2020s.[36,37] However, these developments have also raised ethical concerns relating to safety, regulation, bias, and privacy.[38]

In healthcare, AI is increasingly applied in diagnostics, treatment planning, drug development, personalized medicine, patient monitoring, and healthcare management.[28,29] AI assists clinicians by processing large volumes of medical data and improving diagnostic accuracy and efficiency.[35] Applications include radiology, disease prediction, drug interaction detection, telemedicine, and workload management.[30-34] AI systems such as AlphaFold have significantly advanced protein structure prediction and drug discovery.[34,35] AI chatbots including Woebot, Wysa, and ChatGPT are also being used for mental health support and patient education.[31]

AI has demonstrated important clinical applications across several medical specialties. In cardiovascular medicine, AI improves diagnosis, risk stratification, and prediction of treatment outcomes.[28,29] In dermatology, AI assists in skin cancer detection and management of cosmetic and inflammatory conditions.[37-41] Gastroenterology uses AI in endoscopy and disease monitoring, while infectious disease applications include COVID-19 surveillance, antimicrobial resistance monitoring, and malaria detection.[34-36] AI is also used in neurology, oncology, ophthalmology, pathology, pharmacy, radiology, psychiatry, and primary care to improve diagnostic performance, predict outcomes, and support patient management.[39-44] Despite these advancements, concerns remain regarding reproducibility, external validation, ethical issues, and lack of empathy in AI-assisted healthcare.[31-33]

AI chatbots have emerged as important tools for delivering health information.[41] These chatbots use technologies such as natural language processing (NLP), machine learning, and data analytics to provide users with information about symptoms, medications, preventive care, and lifestyle practices.[48,49] Health chatbots may function as informational tools, symptom checkers, treatment-support systems, mental health assistants, behavioral coaching tools, or integrated healthcare-system assistants connected to electronic health records.[50–56] Their popularity among students and digital natives is largely due to their accessibility, anonymity, 24-hour availability, and integration into smartphones, social media, and messaging platforms.[45–50] Universities increasingly use chatbots for health reminders, wellness support, and personalized guidance.[51,52]

Despite their benefits, AI chatbots have important limitations and risks.[53] Incorrect, outdated, or biased information may lead to misinformation, delayed treatment, or inappropriate self-care practices.[54] Many consumer chatbots lack proper clinical validation and may provide inconsistent or inaccurate recommendations.[55,56] Chatbots also have difficulty considering individual patient differences such as allergies, comorbidities, cultural factors, and psychosocial circumstances.[57–59] Concerns regarding privacy, confidentiality, and data security are also significant because chatbots process sensitive health information.[47,48] Furthermore, AI chatbots cannot fully replace human empathy, judgment, or emotional support, particularly in sensitive mental health situations.[51] Excessive dependence on chatbots may encourage self-medication and delay professional healthcare-seeking behavior.[45,60]

Self-medication refers to the use of medicines or other substances without professional medical supervision to treat self-recognized symptoms or conditions.[61] It commonly involves over-the-counter medications, dietary supplements, alcohol, nicotine, and psychoactive substances.[61–64] Self-medication may arise from healthcare costs, limited access to medical care, or personal beliefs, but it can result in harmful consequences including drug misuse, addiction, adverse reactions, and antimicrobial resistance.[65]

The Self-Medication Hypothesis (SMH) explains that individuals select specific substances based on their psychological needs and emotional distress.[61,62] According to Khantzian, drugs are often used to relieve emotional suffering or psychiatric symptoms, while Duncan emphasized the roles of reinforcement, withdrawal avoidance, and environmental factors in substance dependence.[64,70] Common substances used for self-medication include depressants, stimulants, opioids, nicotine, and cannabis.[61–79] Although these substances may provide temporary relief from anxiety, depression, ADHD symptoms, or psychological pain, prolonged use often worsens mental health conditions and increases addiction risk.[61–69]

Self-medication has significant public health implications, particularly in relation to infectious diseases and antibiotic misuse.[61,62] Self-medication with antibiotics contributes substantially to antimicrobial resistance worldwide.[63] Lack of healthcare access, financial constraints, and inadequate awareness often drive inappropriate antibiotic use.[64] Such practices may lead to treatment failure, allergic reactions, worsening infections, and increased mortality.[65] Misuse of over-the-counter medications such as paracetamol or ibuprofen may also result in serious complications including liver damage or gastrointestinal bleeding.[69]

2.2 THEORETICAL FRAMEWORK

The research is informed by two complementary theoretical models namely the Health Belief Model (HBM) and the Technology Acceptance Model (TAM) model. These models can help to understand the rationale behind students self-medicated through the help of AI chatbots and how their knowledge and attitudes affect their behavior.

Health Belief Model (HBM)

Health Belief Model is one of the most commonly used frameworks that can be applied to understand health-related behaviors that were developed in the 1950s.[80,81] It assumes that people will have higher likelihood to do a certain health action when they perceive themselves to be under threat of a given health issue, feel that the health issue has severe effects, feel that action to be undertaken will minimize the risk or severity, and have perceived fewer barriers to doing so.[81,82] Behavior is also determined by other elements, including cues to action and self-efficacy. Action triggers are triggers, and they can be internal, such as having symptoms, or external, such as peer or digital prompts. Self-efficacy describes the belief of an individual on their capacity to perform the health behavior in an efficient manner.[83]

The use of AI chatbots in self-medication among undergraduate students can be explained using HBM. Students can feel that they are vulnerable to small-time diseases like headaches, colds, or stomach upsets that are prevalent among university populations.[84] In case they take these diseases to be severe and deserving of intervention but can be resolved with an over-the-counter drug, they can seek the help of AI chatbots. The perceived advantages of AI chatbot use are the availability of quick health information, convenience, and anonymity which can motivate students to adopt these tools instead of getting a medical consultation face-to-face.[85] On the other hand, perceived obstacles, including skepticism towards the accuracy of chatbots, distrust in online advice, fear of errors when taking medicine, etc., may restrict use.[86]

Information regarding AI chatbots is crucial in the development of health beliefs. The more students know about the functionality of AI chatbots, their constraints, and the dangers of receiving erroneous guidance, the more they will not perceive the perceived advantages and drawbacks differently as compared to students with little knowledge.[85] An example is a student who realizes that AI chatbots can be ineffective with complex medical cases or drug interactions can be more interested in self-medication using AI chatbots. The attitudes to AI chatbots are also interactive with HBM constructs. Increasing perceived benefits and self-efficacy with positive attitude and decreasing perceived barriers with negative attitudes may be more likely.[86] Action indicators here can be notifications by health applications, advice given by friends or online communities, and, in the past, positive feedback in the use of chatbots.

Technology Acceptance Model (TAM)

Although HBM provides an explanation of the health-related reasons to use AI chatbots, the Technology Acceptance Model serves as a complementary approach since it is concerned with the technology adoption and consumption.[87] As it was developed by Davis in 1989, TAM is based on the assumption that the perceived ease of use and perceived usefulness are the key factors influencing the decision to accept and use a given technology.[87,88] Perceived usefulness is a concept used to define how much an individual is convinced there will be an improvement in performance when they use a technology or how they will attain the desired results. Perceived ease of use is the extent to which the person feels that he or she will have to put little effort in order to use the technology.[88]

When applied to AI chatbots, TAM implies that undergraduate students will be more willing to use such tools in case they assume that the chatbots have useful, accurate, and actionable health suggestions. The students who find chatbots to be effective in supporting them to cope with minor health problems may be more prepared to use chatbots on a regular basis.[89] On the same note, students who feel comfortable using the chatbots, with easy-to-follow instructions and user-friendly interfaces, would tend to use these tools as self-medication.[89] Perceived ease of use is affected by such factors as digital literacy, previous experience with AI technology, and knowledge of smartphones and online applications.[89]

The attitudes towards AI chatbots are associated with TAM constructs. Students who have positive attitudes might view the tools as very helpful and convenient to operate, which will increase their activity and make them use chatbot advice frequently. On the other hand, students having negative attitudes might feel that low usefulness or difficulty when using chatbot systems, which decreases the probability of use.[87] According to TAM, behavioral intention is a good predictor of real use of technology. Behavioral intention in this study is converted to the choice of using AI chatbots in regard to self-medication.

Integration of HBM and TAM

Combining the Health Belief Model and Technology Acceptance Model, the research will be able to investigate the unified effect of health beliefs and technology acceptance on self-medication behaviors among students.[80,86] Information on AI chatbots and their boundaries is a source of perceived benefits in HBM and perceived usefulness in TAM. Indicatively, when students learn that chatbots could give them guidance on the manifestations that are common and not to diagnose them, they would be able to weight the advantages and risks in a better way.[84,87] In the same manner, self-efficacy in HBM and ease of use in TAM are influenced by attitude towards AI chatbots. Effective interactions with chatbots could encourage trust and acceptance of their use without harm, and negative experiences could change or deter the willingness to use them.[85,88]

Access to environmental and contextual factors, including access to technology, the availability of internet services, and social forces are the other crucial thematic issues in the integration of these models. Indicatively, AI chatbots might be easier to use by students who have unlimited access to smartphones and reliable internet connection because of the sense of ease of use. Social media conversation or peer recommendation can become an indicator of action prompting use even in the less knowledgeable students regarding their health.[89] Equally, health beliefs and technology acceptance can be influenced by cultural norms and having been introduced to the practice of self-medication.

2.3 POLICY FRAMEWORK

Nigeria currently does not yet have a comprehensive, standalone legal framework specifically designed to regulate artificial intelligence systems, including AI chatbots, despite the rapid growth of AI adoption across different sectors.[31–33] Instead, the governance of AI technologies is indirectly covered under broader digital economy policies, cybersecurity regulations, and data protection laws. For example, the Nigeria Data Protection Act provides general guidance on personal data handling and privacy protection, which may apply to AI systems that process user information, but it does not specifically address AI decision-making, accountability, or clinical/health-related applications.[34–36] Similarly, existing cybersecurity and ICT policies provide general oversight for digital technologies but do not contain AI-specific provisions that regulate chatbot outputs, medical advice generation, or algorithmic transparency.[37–38]

Efforts toward establishing a structured AI governance system in Nigeria are still at an early stage. The National Information Technology Development Agency (NITDA) has proposed strategic frameworks such as the National Artificial Intelligence Strategy and related policy drafts aimed at promoting responsible AI development, innovation, and ethical use.[39–41] These initiatives emphasize principles such as fairness, transparency, accountability, and safety in AI deployment; however, they remain largely developmental and have not yet been fully enacted into binding legislation.[42–44] Consequently, there is still no enforceable national regulatory framework that specifically governs the use of AI chatbots in sensitive areas such as healthcare information dissemination, self-diagnosis, or self-medication guidance.[45–46]

This regulatory gap has raised concerns among scholars and policymakers regarding the safe integration of AI into everyday decision-making processes, particularly in health-related contexts.[47–49] Without clear legal standards or enforcement mechanisms, AI chatbot outputs may vary in accuracy, reliability, and safety, increasing the risk of misinformation and inappropriate health behaviors, including self-medication.[50–52] Furthermore, issues such as algorithmic accountability, liability for incorrect medical advice, and ethical use of AI in student populations remain insufficiently addressed within the Nigerian regulatory landscape.[53–55] This is particularly important given the increasing reliance of young adults and undergraduate students on AI tools for academic and health-related decision-making.[56–58]

In addition, institutional-level guidelines on AI use within Nigerian universities are still limited or inconsistently implemented.[59–61] Most students engage with AI chatbots based on personal discretion rather than standardized institutional policies or digital literacy training programs.[62–64]

This contributes to variability in usage patterns and increases the likelihood of inappropriate reliance on AI-generated health advice without professional consultation.[65–67] Therefore, the absence of a unified national AI policy framework, combined with weak institutional regulation, represents a significant gap in ensuring the safe, ethical, and responsible use of AI chatbots in Nigeria, particularly within the context of healthcare-related decision-making and self-medication practices among undergraduate students.[68–69]

2.4 CONCEPTUAL FRAMEWORK

This study conceptualizes the use of artificial intelligence (AI) chatbots for self-medication among undergraduate students as a multi-dimensional phenomenon arising from the interaction between individual characteristics, digital exposure, knowledge, attitudes, and socio-environmental factors. These components are aligned with the specific objectives of the study, which include assessing knowledge, attitudes, prevalence of use, and identifying factors influencing the use of AI chatbots for self-medication among undergraduate students.[28]

Self-medication refers to the use of medicines or health-related decisions made by individuals without professional medical consultation. In the context of this study, it includes the use of AI chatbots to obtain advice on symptoms, possible diagnoses, and treatment options without consulting healthcare professionals. This practice has become increasingly common with the rise of AI tools such as ChatGPT and Gemini, which provide instant health-related responses.[29]

Undergraduate students are individuals enrolled in tertiary institutions who are frequently exposed to digital technologies and social media platforms. Their high level of internet use makes them more likely to interact with AI chatbots for academic and health-related purposes, including self-medication.[30]

Knowledge and attitudes toward AI chatbots play a central role in determining usage for self-medication. Knowledge refers to the level of awareness and understanding of AI chatbot functions, benefits, and limitations in providing health information. Students with good knowledge are more likely to critically evaluate chatbot responses and either adopt or avoid using them for self-medication. Attitude refers to the perception and feelings toward AI chatbot use in health-related decision-making. Positive attitudes, such as perceiving chatbots as convenient, accessible, and time-saving, increase the likelihood of use, while concerns about accuracy, safety, and reliability may reduce usage or promote cautious engagement.[31]

The prevalence of AI chatbot use for self-medication represents the proportion of students who have used AI chatbots for health-related decision-making without consulting healthcare professionals. This includes seeking advice on symptoms, possible diagnoses, and treatment options. The level of prevalence is influenced by both individual and environmental factors, including exposure to digital platforms and frequency of internet use.[33]

Influencing factors include socio-demographic characteristics such as age, sex, academic level, and guardians' occupation, as well as behavioral factors such as time spent on social media and exposure to digital health information. Students whose guardians are in higher-skilled occupations may have better access to technology and improved digital literacy, which can enhance knowledge and increase the likelihood of AI chatbot use. Similarly, higher social media engagement increases exposure to AI-generated health content, thereby influencing self-medication behavior.[46]

These components are interrelated. For example, adequate knowledge improves attitude formation, which in turn influences the likelihood of using AI chatbots for self-medication. Socio-demographic and digital exposure factors shape both knowledge and attitude, while these jointly determine actual usage behavior. Increased exposure to AI chatbots may normalize their use for health-related decisions, thereby increasing the risk of self-medication among students.[47]

Knowledge of AI chatbots is fundamental to how students interpret and respond to AI-generated health information. Awareness of limitations such as lack of clinical validation and potential for misinformation may reduce unsafe use. Conversely, limited knowledge may lead to overreliance on AI chatbots for medical decision-making.[48]

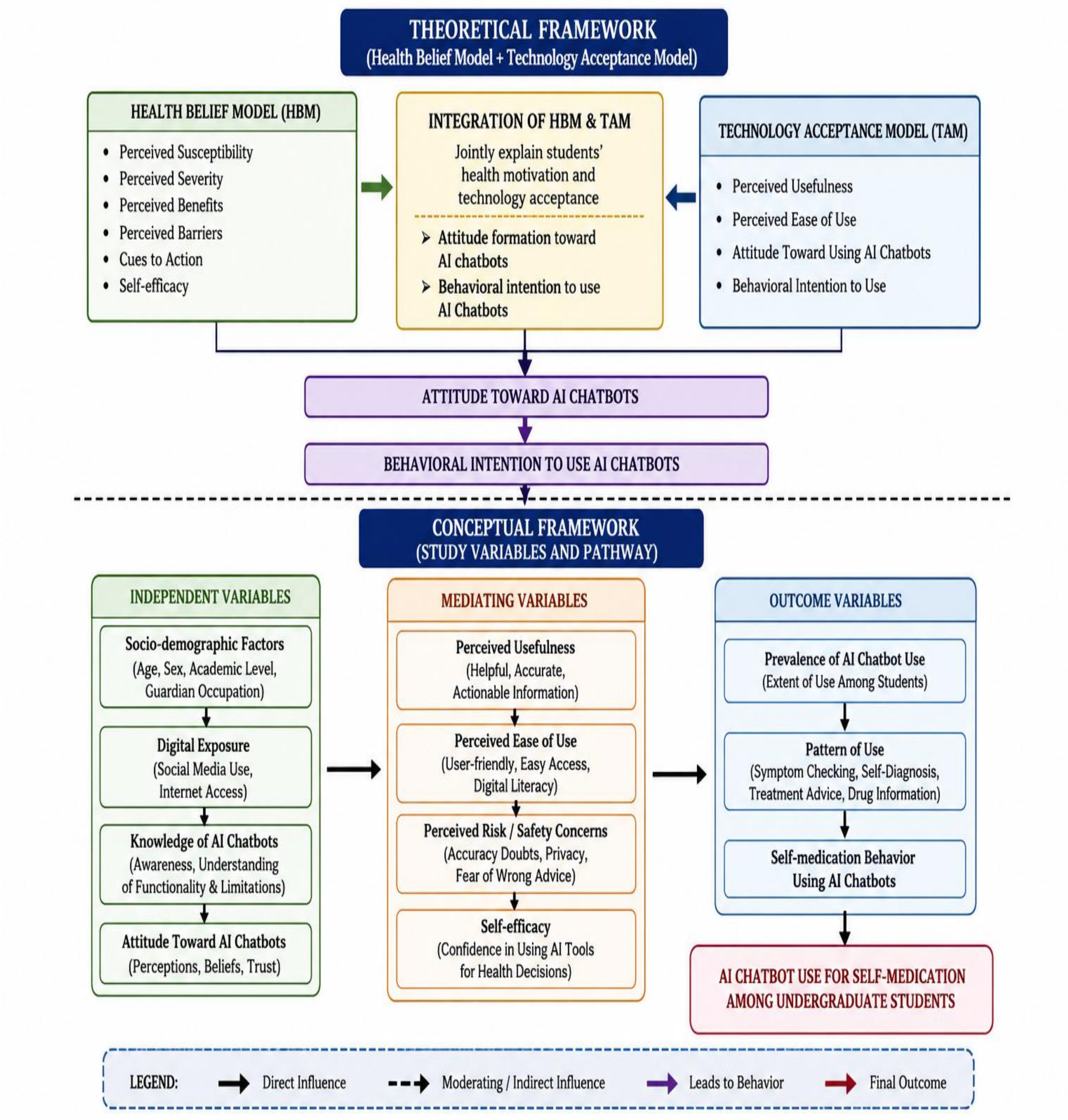
The Technology Acceptance Model (TAM) provides a useful theoretical explanation for this framework. It suggests that perceived usefulness and perceived ease of use influence attitudes, which subsequently determine behavioral intention and actual use. In this context, students who perceive AI chatbots as useful and easy to use are more likely to develop positive attitudes and use them for self-medication.[49]

There is also an implicit relationship between attitude and usage behavior. Positive attitudes toward AI chatbots increase the likelihood of self-medication practices, while concerns about safety and reliability may moderate usage. However, increasing accessibility and frequent exposure may still lead to usage even among students with cautious attitudes.[50]

Both individual and environmental factors influence AI chatbot use for self-medication. Individual factors include knowledge, attitudes, digital literacy, and personal beliefs, while environmental factors include internet access, social media influence, peer influence, and academic exposure. These factors collectively shape students' decision-making processes regarding health information seeking and self-medication behavior.[51]

Overall, the conceptual framework illustrates that the use of AI chatbots for self-medication among undergraduate students is not an isolated behavior but the outcome of interacting cognitive, behavioral, and socio-environmental determinants

FIGURE 1: Conceptual and Theoretical framework



2.5 EMPIRICAL REVIEW

2.5.1 Undergraduate students' knowledge of AI chatbots used for healthrelated purposes

A number of studies have studied the knowledge of the undergraduate students on AI chatbots utilized in health-related contexts and their differences in awareness, familiarity, and understanding.

A descriptive cross sectional study conducted in 2024 explored the application of ChatGPT in health care students, noting that ChatGPT was not intended to be used in medical fields but had possible advantages based on the knowledge and acceptance of the users. The cross-sectional survey that was used in the global study was carried out in the month of May and June 2023 on the students of medicine, nursing, dentistry, nutrition, and laboratory science pooled in the Americas. The responses in terms of categories were compared with descriptive analysis, chi-square tests, and ANOVA. The self-reported knowledge level was of a minimal level (median 2.00, IQR 1.003.00). The majority of the respondents remained neutral on matters concerning ethics with median of 2.61 (IQR 2.113.11) on the topic of whether the use of ChatGPT was ethical or unethical. In most cases, the participants found that ChatGPT could be useful in health care practice, offer reliable information, help to obtain clinical and educational data and simplify work (median 3.89, IQR 3.44–4.34). An estimated 70 percent said they used ChatGPT on their educational work. The research concluded that the perceived knowledge and positive ethical perceptions had a strong relationship with positive attitudes towards ChatGPT, such as the perception of this technology as reliable and helpful in a medical setting.[14]

A 2025 cross sectional study study in South Africa involving undergraduate students in Africa investigated the preferences of students in terms of interacting with a hypothetic AI-powered health care assistant (AIPHA). The experiment in the study was a discrete choice study in June through August 2024 involving 300 adult university students. All the participants rated 10 sets of choices, choosing preferred options according to eight attributes which included cost, confidentiality, security, health care topics, language, persona, access, and services. According to the conditional logit model, the most significant variables that contributed to the engagement of students were language, security, and personalized advice. Students would rather communicate using one of the South African languages instead of using English alone and preferred health information that would be based on local conditions such as the clinics in the area. Such outcomes showed that knowledge and comprehension of AI chatbots among the students were determined not solely by technical familiarity but also by contextual relevance, confidentiality, and accessibility.[15]

In Nigeria, other studies have also investigated the knowledge of AI chatbots in undergraduate programs in health-related learning. An Afe Babalola University, Ado-Ekiti (ABUAD) study in 2024, investigated the knowledge, familiarity and perceptions of AI tools that use chat in pharmacy students. It was a cross-sectional online survey of 252 students conducted in March-April of 2024. The majority of participants were women (72.2%), and accustomed to AI chatbots (88% out of 222), and ChatGPT was the most used tool (82.8) in assignments and studying. The perceptions were mostly positive as 85.3 percent of the students stated that AI tools improved academic performance. Nevertheless, the issues of possible distraction (65.7%) and academic dishonesty (65.1%) were also mentioned. The increased knowledge rates were correlated with the previous education on AI, the level of study and previous knowledge of chat-based AI applications. It was determined by the study that students had high levels of knowledge and mostly positive attitudes towards AI chatbots and the necessity of formal AI education in the pharmacy curriculum was identified.[19]

Another Nigerian study (2024) conducted a study to determine knowledge of ChatGPT among medical, dental, and allied health students. A mixed-methods design would include self-administered structured questionnaires done to 420 students and then in depth interviews done to a sub-sample of 20 students. An estimated 77.4 percent had moderate to excellent ChatGPT knowledge. The majority of the respondents (61.9%, n = 260) mentioned that they used ChatGPT in their studies, and mostly were driven by ease of use (75.0%) and efficiency (72.1%). Risk of dependence (65.0%), inaccuracy (49.7%), concerns about reliability (49.3%), and ethical concerns (41.7%) were the main areas of concern. The analysis of logistic regression revealed that males, older students (not younger than 25 years old), final-year students, and students with prior knowledge or positive attitudes were more likely to use ChatGPT. Findings based on qualitative data supported the issues of errors, ethics, and the inability of infrastructure. The paper emphasized that there was moderate interaction and awareness among the Nigerian health students and that special AI education would be necessary to promote awareness and responsible behavior in health education.[20]

2.5.2 Attitudes toward the use of AI chatbots in making self-medication decisions

A cross sectional study of AI chatbot attitudes in the Arab world was conducted in 2025. A total of 21 countries aged 12 years and older had to complete an online questionnaire between May and June 2024. The questionnaire has evaluated demographics, awareness of AI chatbots, attitudes, and the use patterns of chatbots in the healthcare context. Out of 12886 valid responses, the median age was 24 years old, and the ratio between females and males was 2:1. Majority of them were single, university-educated, urban-based or healthcare-affiliated. Consciousness of AI chatbots was 72.5% though only 26.4% utilized them with predominant use being in health coaching, self-medication, self-diagnosis, and mental health guidance. The most used tool in healthcare assistance was ChatGPT. Chatbots were more frequently used by people having psychological or mental health issues. The attendance in training involving AI significantly anticipated the use of chatbots, and trained members were over three times more likely to use chatbots. The research showed that the attitudes of the students were mixed, with some adopting chatbots in self-medication, and others being afraid of accuracy and reliability.[18]

A 2025 study in Zambia compared pharmacy students with the attitude towards ChatGPT. The cross-sectional research employed a structured questionnaire on the basis of Technology Acceptance Model Edited to Assess ChatGPT Adoption (TAME-ChatGPT) and was performed in February through May 2024. There were 385 responses that were analyzed. ChatGPT had been heard of by the majority of students (93%), and was used by 78.7%. Four items were used in the measurement of attitudes, which are in the form of positive or negative. Univariate analyses indicated that low perceived risk, low anxiety and high technology or social influence had significant positive association with positive attitudes with social influence being the strongest predictor of the regression analysis. Likewise, usage was affected by perceived usefulness. The researchers also emphasized that the positive attitude of students towards AI chatbots in healthcare and self- medications was directly associated with social and technological factors, as well as the achievement of the usefulness of the tool in both academic and practical settings.[23]

In 2023, another Nigerian study was conducted at Ekiti State University to determine perceptions and acceptance of medical chatbots by undergraduate students. The research employed a cross-sectional survey consisting of 300 students in a descriptive study and a semi-structured questionnaire, which was expertly validated and confirmed in terms of public health and measurements. There was equal gender representation and the majority of the participants were between the age of 18 and 25. The research showed the positive attitude to the use of medical chatbots and stated that students had no objections to the usage of chatbots. Nevertheless, it was feared that the health advice offered by chatbots was inaccurate and unreliable. The study highlighted that students were open to AI chatbots, however, more attempts were required to enhance their perception and confidence towards the technology especially when it comes to health-related decision-making.[21]

In a 2025 study, Abia State University, Nigeria, researchers studied attitudes of the use of AI among medical students. The participants of the study were 342 students, and the research method was a structured questionnaire. Although 66.4 percent dismissed the idea of AI taking the place of physicians, 55.9 percent showed the positive tendency towards AI. The attitude of male students was more positive, and AI tools were more often used by clinical students. The results have shown that students generally believed that AI chatbots could be used in healthcare: self-medication, but they were concerned about their effect on clinical decision-making.[22]

2.5.3 Prevalence of AI chatbot use in facilitating self-medication practices

In 2024, an American study investigated the reasons and the use of ChatGPT in online health information (OHI) and the features of the users who were most likely to use the website. The research involved a cross-sectional survey where ResearchMatch platform was used to invite people to fill a web-based survey. The number of respondents who used ChatGPT to OHI was 2,406 (21.5 percent), and 517 (21.5 percent) were respondents who said that they use ChatGPT. The users of ChatGPT were mostly younger than the nonusers and had a lower percentage of higher education. They also complained about increased consumption of transient healthcare services, such as emergency and urgent healthcare. The majority of the users wanted to use

ChatGPT at least two or three times a week or more often, to find out whether or not they needed a medical appointment or to research more about other possible options. ChatGPT was typically considered as helpful by users as the other sources of OHI and their medical professionals. Approximately one-third of the participants took ChatGPT advice and requested referrals or changed medications. Although this was the case, the majority of users were doubtful about the output with the majority of them requiring physician assurances. This paper has shown that AI-based health information affected self-medication, and that chatbots would play a crucial part in health-seeking behaviors.[90]

A 2025 study in Uganda evaluated the use of ChatGPT and other AI-based tools by medical students in four state colleges. The study was a descriptive cross sectional study where the data was gathered between November and December 2023 using a semi-structured questionnaire. The number of students who took part was 564, 93% of whom said they were aware of AI tools, and 75.7% of them had used these tools. The most popular AI tool was ChatGPT (72.2%), then SnapChat AI, Bing AI and Bard AI. The academic applications of AI tools by students mostly included doing tasks, attending tutorials, exam preparation, writing research papers. Other students also applied AI tools in nonacademic aspects, such as emotional support, recreation, and spiritual development. Students younger in age were more likely to use AI tools than older students and students enrolled in Makerere University used AI tools more frequently than Gulu University students. The research indicated that ChatGPT is heavily used by medical students in Uganda and proposed that the students involved in using AI can access both educational and personal health-related applications, which may influence self-medication habits.[91]

A 2024 study in Nigeria assessed the use of chat-based AI tools in pharmacy students of Afe Babalola University, Ado-Ekiti (ABUAD). The researchers carried out a cross-sectional survey (online survey) among 252 undergraduate students. The majority of students (88% n= 222) were conversant with AI tools, and chat GPT was most commonly used (82.8) when doing assignments and study. There were some fears of possible distractions (65.7%) and academic dishonesty (65.1%). Although the research was mainly based on academic use, it was indicated that the level of familiarity and regular use of ChatGPT was high so that students were also likely to refer to AI chatbots as the sources of information, which is applicable to self-medication or health decision-making. The study highlighted the necessity to include AI education in the pharmacy curriculum to make students responsible in using AI tools, including health-related causes and effects.[19]

Past research in Nigeria has also documented self-medication. In a 2021 community-based survey, 1,089 respondents in 6 geopolitical zones were surveyed on the practice of self-medication. The prevalence rate of self-medication was 69.4 in general. Some of the most frequent illnesses that were used by the participants as a means of self-medication included headaches, febrile diseases like malaria, coughs and upper respiratory tract infections, as well as body pains. Examples of self-medication reasons were distance to health care facilities, long queues, convenience, financial reasons, and time saving. The major source of medications was community pharmacies or patent medicine stores. It is not a specific research on AI devices; however, it helped to place this research on the background of the possible impact of AI chatbots on self-medication. With the appearance of AI tools, like ChatGPT, the latter can be used to complement or replace the traditional sources of health information and may influence the way young adults and students self-medicate.[13]

2.5.4 Factors associated with AI chatbot use

In a 2025 research in the United States, the determinants of intentions to use ChatGPT in higher education among university students were investigated. The technology acceptance model, the theory of reasoned action, and the diffusion of innovation theory were implemented in the study survey which surveyed 411 students. With the help of partial least squares structural equation modeling, it was found that the perceived usefulness and subjective norms exerted a significant positive impact on the intention of the students to use ChatGPT. Intention was influenced indirectly through perceived usefulness as influenced by perceived ease of use and trust. The model was useful in explaining about 51 percent of the usage intention variance. The experiment revealed that the willingness of students to use AI chatbots was both dependent on the individual attitude and on the persuasion of peers and the perceived advantages in the academic performance, which emphasizes the importance of social and cognitive variables in adoption.[25]

A 2024 Malaysian study in Southeast Asia investigated the use of AI chatbots in healthcare students. The researchers surveyed 443 undergraduate students in a tertiary healthcare institute to measure the level of knowledge, attitudes, and practices on the use of ChatGPT as an academic tool. Several logistic regression models revealed the effect of age, gender, and academic factors on the use of AI chatbots. ChatGPT was used more frequently by MBBS students than by students of dentistry and allied health sciences. Students in final years were most likely to use academically. More usage was highly related to higher knowledge and positive attitudes. The majority of students were selective users of ChatGPT, utilizing the system to support certain sections of their assignments, although they did the majority of work on their own. A lesser percentage never used it, and some of them over used it. Students additionally expressed their issues related to the accuracy of the data, plagiarism, ethical concerns, and dependency, which proves that socio-demographic and academic determinants influenced adoption and more cautious use of AI tools.[17]

In a study on Chinese medical students, a 2024 study evaluated the use of AI chatbots using the Unified Theory of Acceptance and Use of Technology (UTAUT) model. There were 693 students in 57 universities in 21 provinces that participated in the study. Actual AI chatbot use was only reported by 28.7% and ChatGPT is the most used one. The main purpose to use chatbots was to obtain a quick medical answer and facilitate the learning process by students. Multivariate regression revealed that social influence, enabling conditions, perceived risk, personal innovativeness, and intention to use chatbots had a significant impact on the adoption of chatbots. Students who felt that AI chatbots were convenient, trustworthy, and backed up by their peers or institutions tended to use them. These results brought out the significance of personal characteristics and environmental or academic backgrounds in dictating the usage of chatbots.[16]

In Nigeria, a study carried out in 2025 evaluated the readiness of a group of healthcare students in Obafemi Awolowo University toward AI. To assess the knowledge level, practice exposure, and readiness to use AI in clinical practice the study interviewed 551 students. Although 60 percent students thought they were very high in AI knowledge, only 8 percent of them had adequate knowledge when subjected to objective evaluation. Though the actual exposure was low, students had very positive attitudes toward AI, and the majority (90.8) had a positive view that AI could enhance workflow and 84.4 were willing to take AI training. The level of knowledge had a strong relationship with the willingness to use AI; however, better-informed students were more certain and more aware of AI drawbacks. Students of lower academic stage and exposure had lower readiness to adopt because they had limited clinical experience at the beginning of the year, and academic stage and exposure had a wider range of effects on AI engagement.[26]

In a study covering the Arab countries, 2,240 university students in Iraq, Kuwait, Egypt, Lebanon, and Jordan were studied to assess the adoption of ChatGPT (2024). Only approximately 46.8%

were familiar with ChatGPT and 52.6% said that they had ever used it. Multivariate analysis revealed that socio-demographic and academic variables such as age, country of residence, type of university and recent academic performance played a significant role in chatbot use. Higher adoption was linked with positive attitudes, perceived ease of use, perceived usefulness, social influence, behavioral factors, and low anxiety. The analysis also established that personal and situational factors defined the interest of students in AI chatbots, and it is essential to think about academic and demographic differences when encouraging their use.[27]

CHAPTER THREE

METHODOLOGY

3.1 Study Area

The study was conducted in Benin City, the capital of Edo State, located in the South-South geopolitical zone of Nigeria. Edo State, an inland state in the central southern region of Nigeria, was created in 1991 from the northern part of the former Bendel State. Its capital and largest urban center is Benin City. The state shares boundaries with Kogi State to the northeast, Anambra State to the east, Delta State to the south and southeast, and Ondo State to the west and northwest, while the Niger River runs along its eastern border. The state lies at elevations ranging from about 500 feet (150 m) in the south to over 1,800 feet (550 m) in the north.[92]

According to the 2006 national census, Edo State had a population of 3,233,366, with a gender distribution of 50.5% male and 49.5% female, and an annual growth rate of 3.2%. By 2026, the population was projected to have increased to 5,500,000.[95]

Benin City lies between latitudes 6°14′N and 6°21′N and longitudes 5°35′E and 5°44′E, covering an estimated land area of 1,125 square kilometres. It is situated about 30 kilometres (18.6 miles) from the coast and west of the Niger River. The city is bordered by Ikpoba-Okha to the east, Ovia North East to the north, Uhunmwonde to the west, and Ovia South West to the south. The metropolitan area spans several Local Government Areas, including Oredo, Egor, and Ikpoba-Okha. Common occupations among residents include civil service, artisanal work, and agriculture.[96] Although the Benin ethnic group is dominant, the city also hosts a significant population of non-indigenes.[97] The city is also home to a number of universities including the

University of Benin, Benson Idahosa University, Igbinedion University and Wellspring University.[98]

The research was carried out in the University of Benin (UNIBEN) in Benin City, Edo State, Nigeria. The University of Benin (UNIBEN) is one of Nigeria's foremost federal universities. It was established in 1970 as an Institute of Technology before becoming a full-fledged university in 1971 and adopting its current name in 1972.[99] The university operates two campuses, Ugbowo and Ekehuan, with Ugbowo serving as the main campus. It has 22 faculties, 2 college, and 4 institutes, with a student population exceeding 35,000, the majority of whom are based at the Ugbowo campus.[100]

The Ugbowo campus is situated along the Benin-Lagos Expressway at coordinates 6°20′1.32″N latitude and 5°36′0.53″E longitude.[101] It is bounded to the north by Ekosodin, a major student residential area, to the south by the University of Benin Teaching Hospital (UBTH), to the west by the Edo Development Property Agency (EDPA) Estate, and to the east by the Akiuwa and Edosowan communities.[101]

3.2 Study Design

The research used an analytical cross-sectional survey design. This design is appropriate for assessing the knowledge, attitudes, and prevalence of the use of artificial intelligence chatbots in promoting self-medication among undergraduate students at a single point in time. It enabled gathering of quantitative data about variables of interest and determination of patterns and relationships among knowledge, attitudes, and the use of chatbot.

3.3 Study duration

This study was carried out from December 2024 to May 2026.

3.4 Study Population

The target population was undergraduate students of University of Benin (UNIBEN) in Benin City.

3.5 Selection Criteria

Inclusion Criteria:

- Undergraduate students enrolled in UNIBEN in Benin City.

Exclusion Criteria:

- Undergraduate students who were too ill to participate in the study.
- Students who were not present at time of the study.
- Students who declined to participate in the study.

3.6 Sample Size Determination

The sample size was calculated using Cochran's formula for cross-sectional studies:[102]

$n = (Z^2 * p * (1-p)) / d^2$

Where:

- n = sample size
- Z = standard normal deviate at 95% confidence level (1.96)
- p = estimated prevalence of AI chatbot use among undergraduate students (86%).[92]
- d = margin of error (0.05)

- Design effect = 2

Step 1: Base Sample Size (Cochran's formula)

$$n_0 = \frac{Z^2 \cdot p \cdot (1-p)}{d^2}$$
$$n_0 = \frac{(1.96)^2 \cdot 0.86 \cdot (1-0.86)}{(0.05)^2}$$
$$n_0 = \frac{3.8416 \cdot 0.86 \cdot 0.14}{0.0025}$$
$$n_0 = \frac{3.8416 \cdot 0.1204}{0.0025}$$
$$n_0 = \frac{0.4625}{0.0025} = 185.01 \approx 185$$

Step 2: Apply Design Effect (×2)

$$n = n_0 \times \text{Design Effect} = 185 \times 2 = 370$$

Adjusted sample size (15% non-response):

n = 370 + (15% of 370)

n = 370 + 55.5 ≈ 425.5

Rounded to the nearest whole number, the final sample size is approximately 426.

3.7 Sampling Technique

A multistage sampling technique was employed to select participants for this study due to the large and heterogeneous nature of the undergraduate student population in the University of Benin.

STAGE ONE: SELECTION OF CAMPUS

The University of Benin (UNIBEN) was selected as the study site, representing a federal public university in Benin City, Edo State.

A further selection was made at the campus level within the university. There are 2 campuses in the University of Benin as highlighted above; Ugbowo and Ekehuan campus. One campus (The Ugbowo campus) was selected from these two by means of a simple random sampling method through balloting.

STAGE TWO: SELECTION OF THE FACULTY

A number of faculties were selected using simple random sampling from the list of all faculties and schools in the University of Benin, which include the Faculties of Agriculture, Arts, Education, Engineering, Environmental Sciences, Law, Life Sciences, Management Sciences, Pharmacy, Physical Sciences, Social Sciences, and Veterinary Medicine, as well as the School of Medicine, School of Dentistry, and School of Basic Medical Sciences.

STAGE THREE: SELECTION OF DEPARTMENTS

From each selected faculty, departments were selected using a table of random numbers

STAGE FOUR: SELECTION OF RESPONDENTS

Systematic random sampling was used to select participants from each department. Every third student who met the inclusion criteria and was present during data collection was approached for participation. This continued until the required number from each department was achieved

3.8 DATA MANAGEMENT

3.8.1 Research Tools (Tools for Data Collection)

Data was collected using a structured, self-administered questionnaire adapted and modified from UTAUT and related acceptance models. The questionnaire consisted of both open- and close-ended questions and was organized into five sections with the purpose of collecting the following information.

Section A: Socio-demographic information

This section covered respondent's responses on age, sex, religion, ethnicity, marital status, level of study, faculty, department, place of residence, monthly allowance, guardians level of education, and guardians occupation.

Section B: Knowledge of AI chatbots

This section assessed respondents' knowledge of AI chatbots, source of the information and their knowledge on AI chatbots.

Section C: Attitudes toward AI chatbots in self-medication

This section assessed the various attitudes of the respondents towards AI chatbots.

Section D: Prevalence and frequency of AI chatbot use for self-medication

This section assessed the prevalence of use of AI chatbots for self-medication and the pattern of their use.

Section E: Factors influencing chatbot use

This section explored various factors that may influence use of AI chatbots for self-medication among respondents, including peer influence, internet access, negative implications, and guidelines regulating use of AI chatbots.

3.8.2 Method of Data Collection

Questionnaires were distributed during break periods. Informed consent was obtained, and participants was briefed on the study purpose and privacy measures.

3.8.3 Research Assistants

Two trained research assistants, with Bsc in Computer science supported the study by:

Explaining the study objectives to participants, assisting with questionnaire distribution and collection and ensuring completeness of returned questionnaires

They received a one-day training on study objectives, ethical considerations, and proper data handling.

3.8.4 Pretesting

The questionnaire was pretested on 10% of the calculated sample size among undergraduate students in Benson Idahosa University. Pretesting was conducted to test the questionnaire for correctness and appropriate understanding by the respondents, so as to aid in the appropriate collection of data. This was used to assess clarity, reliability and validity of questions.

3.8.5 Data Analysis

Data was sorted, screened for completeness, coded, and analyzed using IBM SPSS Version 27.0.

3.8.5.1 Scoring of Variables

The occupation of parents/guardians was grouped using the modified International Labor Organization (ILO) classification into skill levels 0-4;

Skill level 1: includes office cleaners, frieght handlers, garden labourers, farmers and kitchen assistants

Skill level 2: includes butchers, bus drivers, account clerks, tailors, shop sales assistants, police officers, hair dressers, building electricians and mechanics

Skill level 3: includes shop managers, medical laboratory technicians, technicians

Skill level 4: includes sales and marketing managers, engineers, teachers, medical practitioners, musicians, theatre nurses and computer systems analysts[104]

Level of knowledge of AI chatbots (12 items)

To determine the level of knowledge of students regarding artificial intelligence chatbots for health information, responses from Section B were analysed. Frequencies and percentages were calculated for dichotomous variables such as "Yes/No" responses, while multiple-response items were summarised by reporting the proportion of respondents selecting each option.

Knowledge was scored by assigning 1 point to each correct response and 0 to the incorrect ones, and the total score for each participant was computed (12 correct responses). These scores were then categorised into levels such as poor and good knowledge.

1. Good knowledge: Score ≥ 70% of total possible points
2. Poor knowledge: Score < 70% of total possible points

Attitudes toward the use of AI chatbots for self-medication (13 items)

To assess attitudes toward the use of AI chatbots for self-medication, data from Section C were analysed using Likert-scale responses. Frequencies, percentages, means, and standard deviations were used to describe responses. Each response was assigned a numerical value ranging:

- 0 = Strongly Disagree / Disagree
- 1 = Agree / Strongly Agree

  with negatively worded items reverse-coded to ensure consistency in interpretation for negatively phrased questions like question number; (21,22,32). A composite attitude score was then calculated for each respondent by summing the individual item scores, and overall attitudes were categorised as negative or positive.

- Positive attitude: Score ≥ 50% of total possible points
- Negative attitude: Score < 50% of total possible points

Prevalence of AI chatbot use for self-medication

The prevalence of AI chatbot use for self-medication was determined using responses from Section D. This involved calculating the proportion of respondents who reported using AI chatbots for self-medication in question; (40). The prevalence was expressed as a percentage of the total number of respondents. In addition, patterns of use such as frequency, types of chatbots used, conditions treated, and perceived outcomes were analysed using descriptive statistics.

Level of utilization was determined using responses from questions;(41,51), where

Often used = 1

Rarely used = 0

A composite score was then calculated for each respondent by summing the individual item scores, and overall utilization was categorised as high or low.

Pattern of AI chatbot use for self-medication was determined using responses from Section D. questions;(42-50)

Factors Influencing Substance Use (4 items)

This section was not scored but was analysed descriptively and cross-tabulated with the outcome of other sections to identify associated factors.

Inferential statistics including the Chi-square test were used to test associations between categorical variables. Where 20% or more of expected cell counts were less than 5, the Fisher-Freeman-Halton Exact Test was applied and the p-value was taken from the Exact Significance (2-sided) output. Backward logistic regression analysis was employed to identify independent predictors of each outcome, controlling for potential confounders. Results were presented using odds ratios (OR) with 95% confidence intervals. Age was entered as a continuous variable in all regression models. A p-value of <0.05 was considered statistically significant.

3.9 Ethical Considerations

The research project was conducted under the guidance of a consulting expert from the Department of Public Health and Community Medicine at the University of Benin Teaching Hospital with Protocol number: ADM/E 22/A/VOL. VII/14865491272106. Ethical approval for the study was obtained from the University of Benin Research Ethics Committee. Participation in the study were voluntary, and all participants provided informed consent after receiving clear information about the study objectives, procedures, and their rights. The participants retained the freedom to discontinue their participation at any point during the process without fear of repercussions or negative consequences. Data confidentiality and privacy was strictly maintained thus no personally identifiable information such as names or addresses were collected through the questionnaires used for data gathering.

Beneficence and Non-maleficence: This study aims to highlight the use of AI chatbots for self-medication including the factors influencing its use. It also seeks to inform university management on the need for effective policies regulating use of AI chatbots. In addition, the study draws attention to the importance of strengthening institutional and broader public health policies on use of AI for self-medication.

3.10 LIMITATIONS TO STUDY

The information that was obtained was based on self-reporting and was therefore subjected to recall bias. Recall bias was overcome by incorporating timelines within the questionnaires, also, the use of simple and clear questions helped to aid the respondents' ability to accurately recall information. Some respondents may have given what they perceived as the most favourable answers, which are contrary to their actual opinions. This can lead to over-reporting or under-reporting.

CHAPTER FOUR

RESULTS

A total of 426 respondents participated in the study with a 100% response rate. The study was carried out in University of Benin (UNIBEN) in Benin City, among undergraduate students.The results are presented in the following sections in line with the specific objectives of the study.

SECTION A: Socio-demographic characteristics of respondents

SECTION B: Knowledge of AI chatbots for self-medication

SECTION C: Attitude toward the use of AI chatbots for self-medication

SECTION D: Prevalence and pattern of AI chatbot use for self-medication

SECTION E: Factors influencing use of AI chatbots for self-medication

SECTION A: SOCIO-DEMOGRAPHIC CHARACTERISTICS

Table 1: Socio-demographic Characteristics of Respondents

Variable	Frequency (n=426)	Percentage (%)
Age Group(years)		
<18	142	33.3
18–24	218	51.2
25–30	58	13.6
>30	8	1.9
Mean age (±SD) 21.50±3.138 years		
Sex		
Male	92	21.6
Female	334	78.4
Religion		
Christianity	397	93.2
Islam	29	6.8
Marital Status		
Single	415	97.4
Married	11	2.6
Ethnic Group		
Edo indigenes	255	59.9
Non-Edo indigenes	171	40.1
Faculty		
Medical Sciences	142	33.3
Non-Medical Sciences	284	66.7
Level of Study		
100 Level	109	25.6
200 Level	86	20.2
300 Level	100	23.5
400 Level	92	21.6
500 Level	26	6.1
600 Level	13	3.1
Residence		
On-campus	347	81.5
Off-campus	79	18.5
Monthly Allowance (₦)		
<10,000	16	3.8
10,000–20,000	57	13.4
21,000–30,000	63	14.8
31,000–50,000	107	25.1
>50,000	183	43.0
Guardian Education		
Primary	4	0.9
Secondary	41	9.6
Tertiary	260	61.0
Postgraduate	117	27.5
Guardian Occupation		
Skill Level 1	31	7.3
Skill Level 2	114	26.8
Skill Level 3	160	37.6
Skill Level 4	121	28.4
Guardian SES		
Low class	56	13.1
Middle class	217	50.9
High class	153	35.9

Table 1 shows the socio-demographic characteristics of the respondents. The majority were aged 18–24 years (51.2%), followed by those less than 18 years (33.3%), 25–30 years (13.6%), and those aged above 30 years (1.9%). Most respondents were female (78.4%), while males accounted for 21.6%. In terms of religion, 93.2% were Christians and 6.8% were Muslims. Almost all respondents were single (97.4%), with a small proportion being married (2.6%). Regarding ethnicity, 59.9% were Edo indigenes, while 40.1% were non-Edo indigenes, with the latter including Yoruba, Igbo, Hausa, Ibibio, Urhobo, and other ethnic groups outside Edo State.

For academic background, 33.3% were in Medical Sciences, while 66.7% were in non-medical faculties. Distribution by level of study showed that 25.6% were in 100 level, 20.2% in 200 level, 23.5% in 300 level, 21.6% in 400 level, 6.1% in 500 level, and 3.1% in 600 level. Most respondents lived on campus (81.5%), while 18.5% lived off campus. Monthly allowance indicated that 3.8% earned less than ₦10,000, 13.4% earned ₦10,000–₦20,000, 14.8% earned ₦21,000–₦30,000, 25.1% earned ₦31,000–₦50,000, and 43.0% earned above ₦50,000.

In relation to parental background, most guardians had tertiary education (61.6%), followed by postgraduate (27.7%), secondary (9.7%), and primary education (0.9%). Guardian occupation, classified using the International Labour Organization ISCO-08 framework, showed that 7.3% were in skill level 1, 26.8% in level 2, 37.6% in level 3, and 28.4% in level 4. Guardian socioeconomic class was distributed as 13.1% low class, 50.9% middle class, and 35.9% high class.

SECTION B: KNOWLEDGE OF ARTIFICIAL INTELLIGENCE (AI) CHATBOTS

Table 2: Awareness and source of information of AI Chatbots among undergraduate students

Variable	Frequency (n = 426)	Percentage (%)
Heard of AI chatbots	426	100.0
Source of knowledge*		
Lectures	104	24.4
Internet	304	71.4
Social media	239	56.1
Friends	162	38.0
Workshops	36	8.5
Online courses	56	13.1
Awareness of UNIBEN AI policy	22	5.2

*** Multiple response**

Table 2 presents the respondents' awareness of AI chatbots. All participants (100.0%) had heard of AI chatbots. The main sources of knowledge were the internet (71.4%), social media (56.1%), lectures (24.4%), friends (38.0%), online courses (13.1%), and workshops (8.5%).

Table 3: Respondents' Knowledge of AI Chatbots

Variable	Frequency (n = 426)	Percentage (%)
AI chatbots are best described as		
AI simulation	393	92.3
Human operators responding to messages	6	1.4
Not sure	27	6.3
Knowledge of chatbots*		
ChatGPT	213	50.0
Gemini	369	86.6
Google Assistant	317	74.4
Siri	312	73.2
Alexa	262	61.5
Ada	31	7.3
Woebot	4	0.9
Medisafe	19	4.5
Received formal training on AI/chatbots	56	13.1
Know AI chatbots can provide information on medicines/health	403	94.6

Table 3 presents the respondents' knowledge of AI chatbots. Most respondents (92.3%) correctly identified AI chatbots as AI simulations, while a small fraction (1.4%) thought they were human operators responding to messages, and 6.3% were unsure. Knowledge of chatbots varied, with Gemini (86.6%), Google Assistant (74.4%), Siri (73.2%), ChatGPT (50.0%), Alexa (61.5%), Ada (7.3%), Medisafe (4.5%), and Woebot (0.9%) being reported. Only 13.1% had received formal training on AI or chatbots, while 86.9% had not. A large majority (94.6%) recognized that AI chatbots can provide information on medicines or health.

Table 4: Correctness of response on knowledge of AI chatbots

Item	Correct Frequency (%)	Incorrect Frequency (%)
AI chatbots are best described as	393 (92.3)	33 (7.7)
Knowledge of chatbots*		
ChatGPT	213 (50.0)	213 (50.0)
Gemini	369 (86.6)	57 (13.4)
Google Assistant	317 (74.4)	109 (25.6)
Siri	312 (73.2)	114 (26.8)
Alexa	262 (61.5)	164 (38.5)
Ada	31 (7.3)	395 (92.7)
Woebot	4 (0.9)	422 (99.1)
Medisafe	407 (95.5)	19 (4.5)
Received formal training on AI/chatbots	56 (13.1)	370 (86.9)
Knowledge that AI chatbots can provide information on medicines/health	403 (94.6)	23 (5.4)

Cronbach's Alpha: 0.739

Table 4 shows respondents' correctness of responses regarding knowledge of AI chatbots. For the description of AI chatbots, most respondents correctly identified them as AI simulations (393, 92.3%), while only a small proportion incorrectly selected human operators responding to messages (6, 1.4%) or were not sure (27, 6.3%).

In terms of knowledge of specific chatbots, correct responses were highest for Gemini (369, 86.6%), followed by Google Assistant (317, 74.4%), Siri (312, 73.2%), and Alexa (262, 61.5%). Half of the respondents correctly identified ChatGPT (213, 50.0%), while correctness was much lower for Ada (31, 7.3%), and Woebot (4, 0.9%), with most respondents incorrectly identifying these tools or lacking awareness. A high proportion of respondents correctly identified Medisafe (407, 95.5%) as not an AI chatbot.

Regarding exposure, only 56 (13.1%) of respondents reported having received formal training on AI/chatbots, while 370 (86.9%) had not. However, a very high proportion (403, 94.6%) correctly acknowledged that AI chatbots can provide information on medicines and health, with only 23 (5.4%) responding incorrectly. The overall internal consistency of the knowledge scale was acceptable, with a Cronbach's alpha of 0.739.

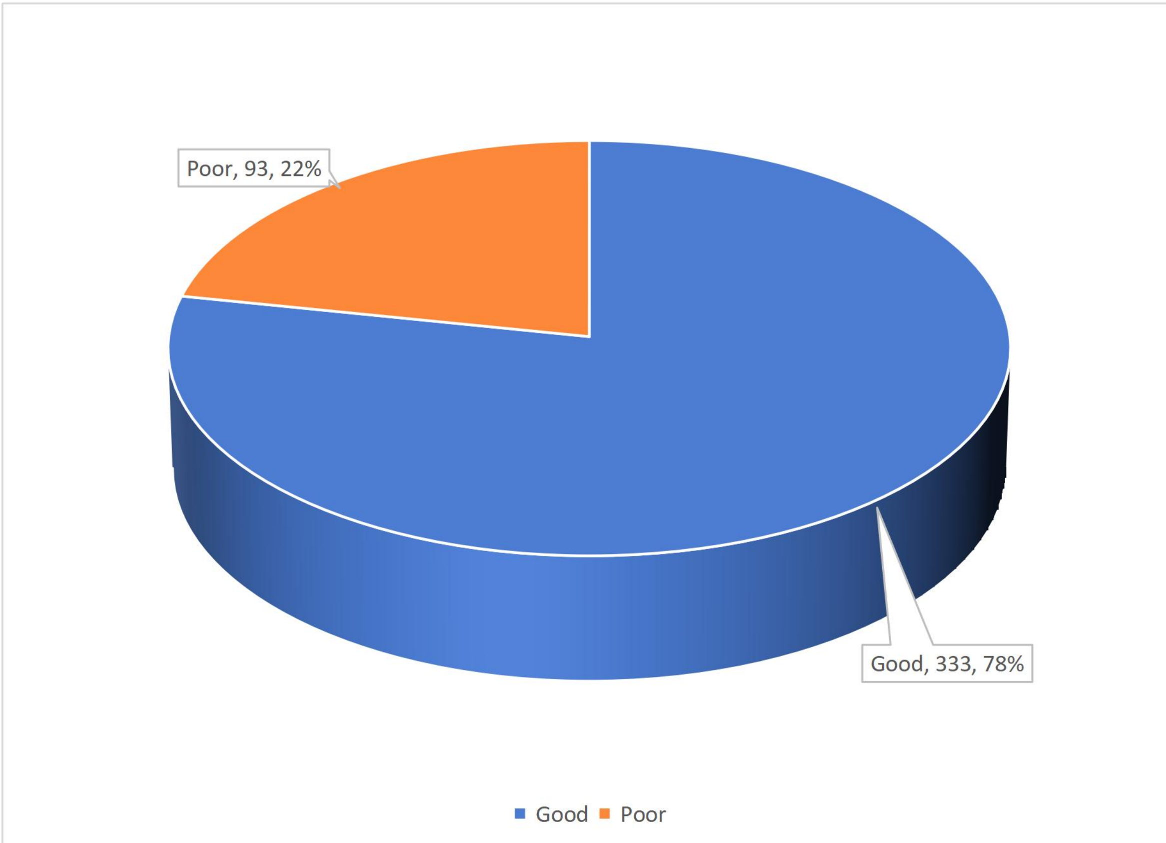


Figure 1. Level of knowledge on AI Chatbot

Overall knowledge grading showed that 78.2% of respondents had good knowledge of AI chatbots, whereas 21.8% had poor knowledge.

Table 5: Relationship between Sociodemographic characteristics and Knowledge of AI chatbots

Variable	Knowledge of AI chatbots		Test statistics	p-value
	Good	Poor		
Age (years)				
<18	109 (76.8)	33 (23.2)	4.711	0.194
18–24	168 (77.1)	50 (22.9)		
25–30	51 (87.9)	7 (12.1)		
>30	5 (62.5)	3 (37.5)		
Sex				
Male	82 (88.9%)	10 (11.1%)	4.343	**0.037***
Female	266 (79.6%)	68 (20.4%)		
Religion				
Christianity	325 (81.9%)	72 (18.1%)	0.118	0.731
Islam	23 (79.3%)	6 (20.7%)		
Marital Status				
Single	341 (82.2%)	74 (17.8%)	2.461	0.117
Married	7 (63.6%)	4 (36.4%)		
Ethnic Group				
Edo indigenes	214 (83.9%)	41 (16.1%)	2.115	0.146
Non-Edo	134 (78.4%)	37 (21.6%)		
Faculty				
Medical Sciences	116 (81.7%)	26 (18.3%)	<0.001	>0.999
Non-Medical Sciences	232 (81.7%)	52 (18.3%)		
Level of Study				
100	79 (72.5)	30 (27.5)	5.792	0.327
200	69 (80.2)	17 (19.8)		
300	76 (76.0)	24 (24.0)		
400	79 (85.9)	13 (14.1)		
500	20 (76.9)	6 (23.1)		
600	10 (76.9)	3 (23.1)		
Place of Residence				
On-campus	281 (81.0%)	66 (19.0%)	0.631	0.427
Off-campus	67 (84.8%)	12 (15.2%)		
Monthly Allowance (₦)				
≤50,000	188 (77.4)	55 (22.6)	8.708	0.069
>50,000	145 (79.2)	38 (20.8)		
Guardian Education				
Primary	2 (50.0)	2 (50.0)	3.924	0.270
Secondary	31 (75.6)	10 (24.4)		
Tertiary	199 (76.5)	61 (23.5)		
Postgraduate	97 (83.0)	20 (17.0)		
Guardian Occupation (ILO)				
Skill 1	20 (64.5%)	11 (35.5%)	15.430	**0.001**
Skill 2	100 (87.7%)	14 (12.3%)		
Skill 3	138 (86.3%)	22 (13.8%)		
Skill 4	90 (74.4%)	31 (25.6%)		
Guardian SES				
Low class	117 (76.5)	36 (23.5)	3.908	0.256
Middle class	192 (88.5)	25 (11.5)		
High class	39 (69.6)	17 (30.4)		

***Fisher exact**

Table 5 shows the relationship between socio-demographic characteristics and knowledge of AI chatbots among respondents. There was no statistically significant association between knowledge level and age ($\chi^2 = 4.711$, $p = 0.194$), religion ($\chi^2 = 0.118$, $p = 0.731$), marital status ($\chi^2 = 2.461$, $p = 0.117$), ethnic group ($\chi^2 = 2.115$, $p = 0.146$), faculty ($\chi^2 = 0.000$, $p > 0.999$), level of study ($\chi^2 = 5.792$, $p = 0.327$), place of residence ($\chi^2 = 0.631$, $p = 0.427$), monthly allowance ($\chi^2 = 8.708$, $p = 0.069$), and guardian education ($\chi^2 = 3.924$, $p = 0.270$).

However, a statistically significant association was observed between sex and knowledge of AI chatbots ($\chi^2 = 4.343$, $p = 0.037$), with males demonstrating higher knowledge levels than females.

In addition, guardian occupation showed a statistically significant association with knowledge of AI chatbots ($\chi^2 = 15.430$, $p = 0.001$), with respondents whose guardians were in higher skill categories generally demonstrating better knowledge. Fisher's exact test was applied where appropriate, and statistical significance was set at $p < 0.05$.

Table 6: Predictors of Knowledge of AI Chatbots

Variable	B	Odds Ratio	95% C.I.		P-value
			Lower	Upper	
Age (years)					
<18		1			
18–24	-0.709	0.492	0.017	14.545	0.681
25–30	-0.324	0.723	0.026	20.455	0.849
>30	0.862	2.368	0.068	82.665	0.634
Sex					
Female		1			
Male	1.610	5.000	1.913	13.072	**0.001**
Religion					
Christianity		1			
Islam	-0.277	0.758	0.152	3.778	0.736
Marital Status					
Single		1			
Married	0.562	1.755	0.171	18.058	0.636
Ethnic Group					
Edo indigenes		1			
Non-Edo	-2.998	0.05	0.001	1.705	0.096
Faculty					
Medical Sciences		1			
Non-Medical Sciences	-1.725	0.178	0.023	1.406	0.102
Level of study					
100		1			
200	0.236	1.266	0.393	4.082	0.692
300	0.429	1.536	0.57	4.14	0.396
400	-2.998	0.05	0.001	1.705	0.096
500	0.801	2.228	0.325	15.251	0.414
600	0.562	1.755	0.171	18.058	0.636
Place of residence					
On-campus		1			
Off-campus	-0.197	0.822	0.303	2.226	0.699
Monthly allowance (naira)					
≤50,000		1			
>50,000	0.429	1.536	0.57	4.14	0.396
Guardian's highest level of education					
Primary		1			
Secondary	-2.998	0.05	0.001	1.705	0.096
Tertiary	0.801	2.228	0.325	15.251	0.414
Postgraduate	-0.64	0.527	0.217	1.279	0.157
Guardian's Occupation (ILO)					
Skill 1		1			
Skill 2	-1.010	0.364	0.141	0.943	**0.038**
Skill 3	0.926	2.525	1.208	5.280	**0.014**
Skill 4	0.939	2.556	1.337	4.888	**0.005**
Guardian SES					
Low class		1			
Middle class	-2.998	0.05	0.001	1.705	0.096
High class	0.801	2.228	0.325	15.251	0.414

*Nagelkerke Pseudo R^2 = 0.165, CI= Confidence Interval, OR= Odds ratio, *- reference category*

Table 6 presents the predictors of knowledge of AI chatbots based on backward logistic regression analysis (Step 11). The final model showed that sex was a significant predictor of knowledge, males were five times more likely to have good knowledge compared to females (OR = 5.000, 95% CI: 1.913–13.072, p = 0.001).

Similarly, guardian occupation was significantly associated with knowledge of AI chatbots. Compared with respondents whose guardians were in Skill Level 1, those in Skill Level 2 had lower odds of good knowledge (OR = 0.364, 95% CI: 0.141–0.943, p = 0.038), while those in Skill Level 3 (OR = 2.525, 95% CI: 1.208–5.280, p = 0.014) and Skill Level 4 (OR = 2.556, 95% CI: 1.337–4.888, p = 0.005) had significantly higher odds of good knowledge.

SECTION C: ATTITUDINAL RESPONSE TOWARD THE USE OF AI CHATBOTS FOR SELF-MEDICATION

Table 7: Respondents' Attitude Towards AI Chatbots

Variable	Attitudinal Responses		
	Disagree	Neutral	Agree
AI chatbots are useful for obtaining drug-related information	296 (69.5)	68 (16.0)	62 (14.6)
AI chatbots provide reliable information for self-medication	209 (49.1)	118 (27.7)	99 (23.2)
AI chatbots make it easier to decide which medicines to use without seeing a doctor	270 (63.4)	70 (16.4)	86 (20.2)
AI chatbots help in understanding drug dosage and instructions	120 (28.2)	85 (20.0)	221 (51.9)
Using AI chatbots for self-medication saves time and money	245 (57.5)	69 (16.2)	112 (26.3)
I feel comfortable discussing minor health problems with AI chatbots	92 (21.6)	94 (22.1)	240 (56.3)
Information from AI chatbots influences my decision to self-medicate	254 (59.6)	71 (16.7)	101 (23.7)
AI chatbots can increase the risk of inappropriate drug use	63 (14.8)	49 (11.5)	314 (73.7)
AI chatbots should not replace healthcare professionals	39 (9.2)	23 (5.4)	364 (85.4)
AI chatbots can support but not replace professional medical advice	34 (8.0)	36 (8.5)	356 (83.6)
AI chatbots have benefits in facilitating self-medication	176 (41.3)	117 (27.5)	133 (31.2)
AI chatbots have drawbacks that may negatively affect health	66 (15.5)	62 (14.6)	298 (70.0)
AI chatbots can completely replace clinical consultation	70 (16.4)	38 (8.9)	318 (74.6)

Cronbach's Alpha: 0.716

Table 7 presents a detailed overview of respondents' attitudes towards AI chatbots, particularly in the context of self-medication. A majority of participants (69.5%) disagreed that AI chatbots are useful for obtaining drug-related information, and 63.4% disagreed that chatbots make it easier to decide which medicines to use without consulting a doctor, while smaller proportions agreed with these statements (14.6% and 20.2%, respectively). In contrast, over half of the respondents (51.9%) agreed that AI chatbots assist in understanding drug dosages and instructions, and 56.3% reported feeling comfortable discussing minor health problems with chatbots. Regarding efficiency, 57.5% agreed that using AI chatbots for self-medication saves time and money, while 59.6% acknowledged that information obtained from chatbots influences their decision to self-medicate. Participants were also aware of the potential risks associated with chatbot use; 73.7% agreed that AI chatbots can increase the risk of inappropriate drug use, and 70.0% recognized that chatbots may have drawbacks that could negatively affect health. Importantly, most respondents emphasized that AI chatbots should not replace healthcare professionals, with 85.4% agreeing that they should not, and 83.6% acknowledging that chatbots can only support, but not replace, professional medical advice. Despite these concerns, 74.6% disagreed with the notion that chatbots can completely replace clinical consultations.

Table 8: Appropriateness of attitudinal response towards AI chatbots use for self-medication

Variable	Attitudinal Responses	
	Appropriate Frequency (%)	Inappropriate Frequency (%)
AI chatbots are useful for obtaining drug-related information	62 (14.6)	364 (85.4)
AI chatbots provide reliable information for self-medication	209 (49.1)	217 (50.9)
AI chatbots make it easier to decide which medicines to use without seeing a doctor	270 (63.4)	156 (36.6)
AI chatbots help in understanding drug dosage and instructions	120 (28.2)	306 (71.8)
Using AI chatbots for self-medication saves time and money	245 (57.5)	181 (42.5)
I feel comfortable discussing minor health problems with AI chatbots	92 (21.6)	334 (78.4)
Information from AI chatbots influences my decision to self-medicate	101 (23.7)	325 (76.3)
AI chatbots can increase the risk of inappropriate drug use	314 (73.7)	112 (26.3)
AI chatbots should not replace healthcare professionals	364 (85.4)	62 (14.6)
AI chatbots can support but not replace professional medical advice	356 (83.6)	70 (16.4)
AI chatbots have benefits in facilitating self-medication	176 (41.3)	250 (58.7)
AI chatbots have drawbacks that may negatively affect health	298 (70.0)	128 (30.0)
AI chatbots can completely replace clinical consultation	70 (16.4)	356 (83.6)

Cronbach's Alpha: 0.716

Table 8 presents the appropriateness of respondents' attitudes towards the use of AI chatbots for self-medication. A relatively small proportion of respondents (62, 14.6%) appropriately agreed that AI chatbots are useful for obtaining drug-related information, while most responses were inappropriate (364, 85.4%). Similarly, only 209 (49.1%) appropriately agreed that chatbots provide reliable information for self-medication, compared to 217 (50.9%) inappropriate responses.

More than half of the respondents appropriately agreed that AI chatbots make it easier to decide which medicines to use without seeing a doctor (270, 63.4%) and that they save time and money (245, 57.5%), while lower proportions were observed for understanding drug dosage and instructions (120, 28.2%) and comfort in discussing minor health problems (92, 21.6%). Only 101 (23.7%) appropriately agreed that chatbot information influences their self-medication decisions.

A higher proportion appropriately recognized potential risks, with 314 (73.7%) agreeing that AI chatbots can increase inappropriate drug use and 298 (70.0%) acknowledging possible negative health effects. Strong agreement was also observed regarding the role limitation of chatbots, as 364 (85.4%) appropriately agreed that they should not replace healthcare professionals, and 356 (83.6%) agreed that they can only support, not replace, professional medical advice. However, only 70 (16.4%) appropriately believed that AI chatbots can completely replace clinical consultation. Overall internal consistency of the attitude scale was acceptable, with a Cronbach's alpha of 0.716.

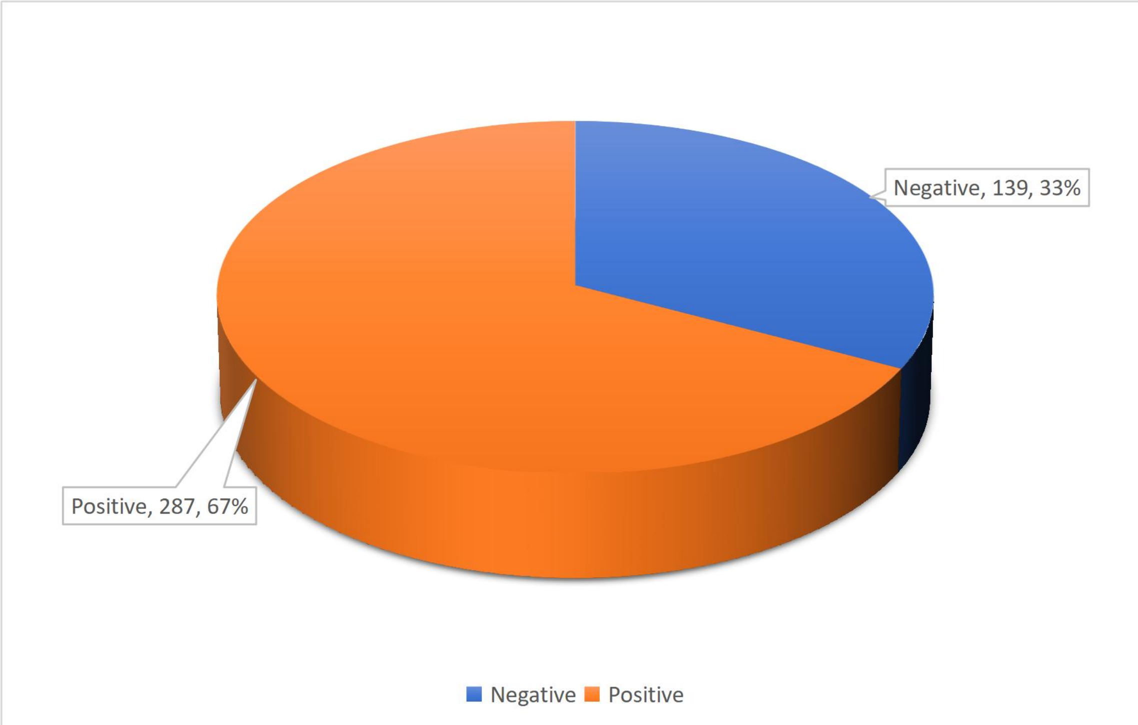


Figure 2. Overall attitude toward AI Chatbot for Self medication

When overall attitude was assessed, 67.4% of respondents demonstrated a positive attitude toward AI chatbots for self-medication, indicating a general openness to their use under appropriate circumstances, while 32.6% held a negative attitude, reflecting caution or skepticism regarding their reliability and safety.

Table 9: Relationship between Sociodemographic characteristics and Attitude towards AI chatbots

Variable	Attitude towards AI chatbots		Test statistics	p-value
	Negative	Positive		
Age (years)				
<18	40 (28.2)	102 (71.8)	7.064	0.070
18–24	83 (38.1)	135 (61.9)		
25–30	13 (22.4)	45 (77.6)		
>30	3 (37.5)	5 (62.5)		
Sex				
Male	26 (28.3%)	66 (71.7%)	1.019	0.313
Female	113 (33.8%)	221 (66.2%)		
Religion				
Christianity	129 (32.5%)	268 (67.5%)	0.049	0.825
Islam	10 (34.5%)	19 (65.5%)		
Marital Status				
Single	135 (32.5%)	280 (67.5%)	0.072	0.789
Married	4 (36.4%)	7 (63.6%)		
Ethnic Group				
Edo	90 (35.3%)	165 (64.7%)	2.052	0.152
Non-Edo	49 (28.7%)	122 (71.3%)		
Faculty				
Medical Sciences	45 (31.7%)	97 (68.3%)	0.085	0.770
Non-Medical Sciences	94 (33.1%)	190 (66.9%)		
Level of Study				
100	41 (37.6)	68 (62.4)	3.924	0.560
200	24 (27.9)	62 (72.1)		
300	33 (33.0)	67 (67.0)		
400	32 (34.8)	60 (65.2)		
500	6 (23.1)	20 (76.9)		
600	3 (23.1)	10 (76.9)		
Place of Residence				
On-campus	109 (31.4%)	238 (68.6%)	1.261	0.262
Off-campus	30 (38.0%)	49 (62.0%)		
Monthly Allowance (₦)				
≤50,000	76 (31.3)	167 (68.7)	5.258	0.262
>50,000	63 (34.4)	120 (65.6)		
Guardian Education				
Primary	4 (100.0)	0 (0.0)	19.925	**<0.001**
Secondary	4 (9.8)	37 (90.2)		
Tertiary	94 (36.2)	166 (63.8)		
Postgraduate	35 (29.9)	82 (70.1)		
Guardian Occupation (ILO)				
Skill 1	4 (12.9%)	27 (87.1%)	18.270	**<0.001**
Skill 2	25 (21.9%)	89 (78.1%)		
Skill 3	58 (36.3%)	102 (63.7%)		
Skill 4	52 (43.0%)	69 (57.0%)		
Guardian SES				
Low class	96 (62.7)	57 (37.3)	19.122	**<0.001**
Middle class	139 (64.1)	78 (35.9)		
High class	52 (92.9)	4 (7.1)		
Knowledge of AI Chatbots				
Good	98 (29.4)	235 (70.6)	7.104	**0.008**
Poor	41 (44.1)	52 (55.9)		

Table 9 shows the relationship between socio-demographic characteristics and attitude towards AI chatbots among respondents. There was no statistically significant association between attitude and age ($\chi^2 = 7.064$, $p = 0.070$), sex ($\chi^2 = 1.019$, $p = 0.313$), religion ($\chi^2 = 0.049$, $p = 0.825$), marital status ($\chi^2 = 0.072$, $p = 0.789$), ethnic group ($\chi^2 = 2.052$, $p = 0.152$), faculty ($\chi^2 = 0.085$, $p = 0.770$), level of study ($\chi^2 = 3.924$, $p = 0.560$), place of residence ($\chi^2 = 1.261$, $p = 0.262$), monthly allowance ($\chi^2 = 5.258$, $p = 0.262$)

However, a statistically significant association was observed between attitude and guardian education ($\chi^2 = 19.925$, $p < 0.001$), guardian occupation ($\chi^2 = 18.270$, $p < 0.001$) and guardian SES($\chi^2 = 19.122$, $p < 0.001$). Respondents whose guardians had higher educational levels, higher occupational skill categories and higher socioeconomic class tended to show more positive attitudes towards AI chatbots. In addition, knowledge of AI chatbots was significantly associated with attitude ($\chi^2 = 7.104$, $p = 0.008$), with respondents who had good knowledge demonstrating more positive attitudes compared to those with poor knowledge. Statistical significance was set at $p < 0.05$.

Table 10: Predictors of positive Attitude towards the use of AI Chatbots for self medication

Variable	B	Odds Ratio	95% C.I.		P-value
			Lower	Upper	
Age					
<18		1			
18–24	0.725	2.064	0.319	13.345	0.447
25–30	-0.032	0.969	0.159	5.912	0.973
>30	0.268	1.308	0.196	8.735	0.782
Sex					
Male		1			
Female	0.426	0.298	1.531	0.687	3.411
Religion					
Christianity		1			
Islam	0.747	0.243	2.11	0.603	7.386
Marital Status					
Single		1			
Married	-0.541	0.627	0.582	0.065	5.182
Ethnic Group					
Edo		1			
Non-Edo	-0.597	0.057	0.487	0.132	1.012
Faculty					
Medical Sciences		1			
Non-Medical Sciences	-0.697	0.058	0.498	0.243	1.023
Level of study					
100		1			
200	-0.084	0.938	0.919	0.111	7.645
300	0.318	0.771	1.374	0.161	11.727
400	0.409	0.711	1.505	0.174	13.029
500	-0.066	0.95	0.936	0.12	7.315
600	0.118	0.927	1.125	0.091	13.931
Place of residence					
On-campus		1			
Off-campus	0.299	0.444	1.349	0.627	2.903
Monthly Allowance (₦)					
≤50,000		1			
>50,000	0.509	1.664	0.917	3.018	0.094
Guardian Education					
Primary		1			
Secondary	-23.621	<0.001	<0.001	<0.001	>0.999
Tertiary	1.030	2.800	0.779	10.063	0.115
Postgraduate	-0.464	0.629	0.367	1.077	0.091
Guardian Occupation (ILO)					
Skill 1		1			
Skill 2	2.709	15.020	3.263	69.132	**0.001**
Skill 3	0.797	2.219	1.149	4.286	**0.018**
Skill 4	0.447	1.564	0.923	2.650	0.096
Guardian SES					
Low class		1			
Middle class	-0.597	0.057	0.487	0.132	1.012
High class	-0.504	0.803	0.602	0.701	
Knowledge of AI Chatbots					
Good		1			
Poor	-0.697	0.058	0.498	0.243	1.023

Nagelkerke Pseudo R^2 =0.177,CI= Confidence Interval,OR= Odds ratio,- reference category*

Table 10 presents the results of the backward logistic regression analysis examining predictors of attitude towards the use of AI chatbots for self-medication. Age was included in the model, with participants aged less than 18 years used as the reference category; however, none of the older age groups showed statistically significant associations with attitude (18–24 years: OR = 2.064, $p = 0.447$; 25–30 years: OR = 0.969, $p = 0.973$; >30 years: OR = 1.308, $p = 0.782$). Monthly allowance (₦) was also assessed, using <₦10,000 as the reference group. Although higher income categories showed varying odds of positive attitude, none reached statistical significance at $p < 0.05$ (10,000–20,000: OR = 0.454, $p = 0.226$; 21,000–30,000: OR = 0.474, $p = 0.060$; 31,000–50,000: OR = 0.657, $p = 0.235$; >50,000: OR = 1.664, $p = 0.094$). Guardian education was included with primary education as the reference group; secondary education showed no meaningful contribution due to extreme coefficient values, while tertiary (OR = 2.800, $p = 0.115$) and postgraduate education (OR = 0.629, $p = 0.091$) were also not statistically significant. In contrast, guardian occupation (ILO classification) demonstrated significant associations with attitude. Compared with Skill Level 1, Skill Level 2 showed a strong positive association with favourable attitude (OR = 15.020, $p = 0.001$), while Skill Level 3 also remained significant (OR = 2.219, $p = 0.018$). Skill Level 4 was not statistically significant (OR = 1.564, $p = 0.096$). Overall, the model indicates that guardian occupation was the most consistent predictor of attitude towards AI chatbot use for self-medication, while other sociodemographic variables showed no significant independent effects.

SECTION D: PREVALENCE AND PATTERN OF AI CHATBOT USE

Table 11: Prevalence and Pattern of AI Chatbot Use

Variable	Frequency	Percentage (%)
Own a mobile device	426	100.0
How often use mobile device(n=426)		
Very often	415	97.4
Often	4	0.9
Occasionally	2	0.5
Rarely	5	1.2
Mobile device usage circumstances*(n=426)		
Social media	382	89.7
Academic purposes	394	92.5
Gaming	212	49.8
Health info	267	62.7
Average time spent on social media daily(n=426)		
<2 hours	117	27.5
≥2 hours	309	72.5
Used AI chatbot for any purpose		
AI chatbot purpose*(n=414)		
Academic work	412	99.5
Social interaction	259	62.6
Entertainment	242	58.4
Health info	287	69.3
Used AI chatbot for health info	370	86.9
Used AI chatbot for self-medication	130	30.5
Frequency of chatbot use for self-medication(n=130)		
Very often	4	3.1
Often	17	13.0
Occasionally	60	46.2
Rarely	49	37.7
Frequency of device use for health purposes(n=130)		
Rarely used	70	53.8
Often used	60	46.2
AI chatbots used (self-medication)* (n=130)		
ChatGPT	130	100.0
Gemini	58	44.6
Google Assistant	23	17.7
Siri	11	8.5
Ada	2	1.5
Woebot	2	1.5
Social media chatbots	8	6.2
Consultation led to self-medication	85	20.0
Chatbot influenced decision to self-medicate	71	16.7
Condition treated using AI Chatbot*(n=130)		
Malaria	29	22.3
Typhoid	8	6.2
Headache	28	21.5
Cough/Cold	30	23.1
Stomach upset	36	27.7
Skin condition	54	41.5
Menstrual pain	41	31.5
Expected health outcome achieved	98	23.0
Experienced negative outcome	11	2.6
Recommendation for self-medication(n=130)		
Definitely Yes	7	5.4
Probably Yes	21	16.2
Not sure	33	25.4
Probably No	38	29.2
Definitely No	31	23.8
Continue using AI chatbots in future	158	37.1

*** multiple-response**

Table 11 summarizes the prevalence and pattern of AI chatbot use among respondents. All respondents (100%) owned a mobile device, with the majority (97.4%) reporting very frequent use. Mobile devices were primarily used for academic purposes (92.5%) and social media (89.7%), with smaller proportions using them for health information (62.7%) or gaming (49.8%). Daily social media use varied, with 27.5% spending <2 hours, and 72.5% spending ≥2 hours online. Nearly all respondents (97.2%) had used an AI chatbot for any purpose, mainly for academic work (96.7%), followed by health information (67.4%), social interaction (60.8%), and entertainment (56.8%). A smaller proportion (30.5%) had used AI chatbots specifically for self-medication, with 20.2% reporting very frequent use. Among those who self-medicated, ChatGPT was the most commonly used chatbot (32.9%), followed by Gemini (13.6%) and Google Assistant (5.4%). Consultations with chatbots led to self-medication in 20% of cases, and chatbot advice influenced self-medication decisions in 16.7% of respondents. Conditions addressed using AI chatbots included skin conditions (12.7%), menstrual pain (9.6%), stomach upset (8.5%), malaria (6.8%), cough/cold (7.0%), headache (6.6%), and typhoid (1.9%). About 23% reported achieving the expected health outcome, while 2.6% experienced negative outcomes. Regarding recommendations for self-medication, 24.6% would definitely recommend it, 14.3% probably would, and 46.7% did not respond or were not applicable. 37.1% indicated they would continue using AI chatbots in the future.

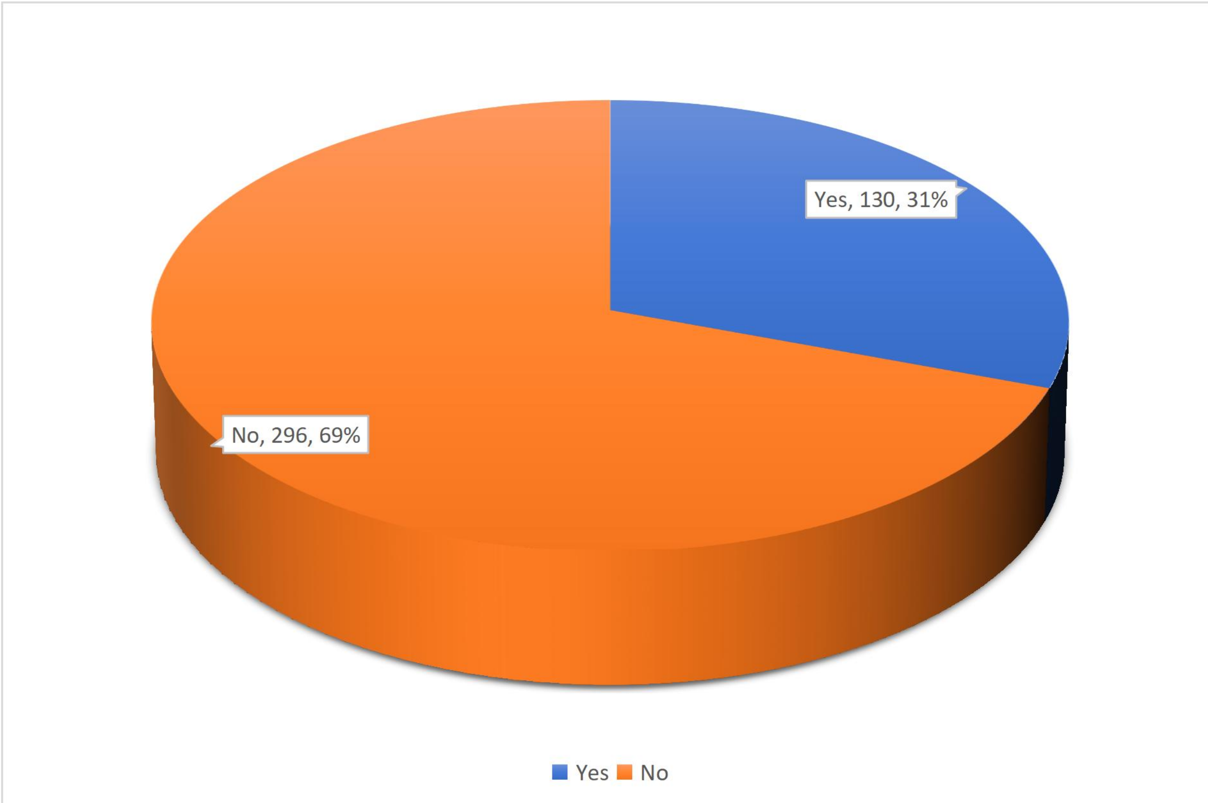


Figure 3: Prevalence of AI chatbot for self-medication

Overall, the prevalence of AI chatbot use for self-medication was 130 (30.5%), with the majority 296 (69.5%) not using chatbots for this purpose.

Table 12: Relationship between Sociodemographic characteristics and Use of AI chatbot for self-medication

Variable	AI Chatbot Use		Test statistics	p-value
	Never	Ever		
Age (years)				
<18	99 (69.7)	43 (30.3)	0.599	0.897
18–24	153 (70.2)	65 (29.8)		
25–30	38 (65.5)	20 (34.5)		
>30	6 (75.0)	2 (25.0)		
Sex				
Male	58 (19.6)	34 (26.2)	2.295	0.130
Female	238 (80.4)	96 (73.8)		
Religion				
Christianity	273 (92.2)	124 (95.4)	1.417	0.234
Islam	23 (7.8)	6 (4.6)		
Marital status				
Single	286 (96.6)	129 (99.2)	2.445	0.118
Married	10 (3.4)	1 (0.8)		
Ethnic group				
Edo indigenes	185 (62.5)	70 (53.8)	2.815	0.093
Non-Edo	111 (37.5)	60 (46.2)		
Faculty				
Medical Sciences	97 (32.8)	45 (34.6)	0.138	0.710
Non-Medical Sciences	199 (67.2)	85 (65.4)		
Level of study				
Year 1	83 (28.0)	26 (20.0)	5.727	0.334
Year 2	55 (18.6)	31 (23.8)		
Year 3	71 (24.0)	29 (22.3)		
Year 4	61 (20.6)	31 (23.8)		
Year 5	19 (6.4)	7 (5.4)		
Year 6	7 (2.4)	6 (4.6)		
Place of residence				
On-campus	247 (83.4)	100 (76.9)	2.544	0.111
Off-campus	49 (16.6)	30 (23.1)		
Monthly allowance(₦)				
≤50,000	175 (72.0)	68 (28.0)	2.519	0.641
>50,000	121 (40.9)	62 (47.7)		
Guardian education				
Primary	4 (1.4)	0 (0.0)	5.051	0.168
Secondary	24 (8.2)	17 (13.1)		
Tertiary	178 (60.3)	82 (63.1)		
Postgraduate	86 (29.1)	31 (23.8)		
Guardian occupation (ILO skill level)				
Skill 1	17 (5.7)	14 (10.8)	9.941	**0.019***
Skill 2	74 (25.0)	40 (30.8)		
Skill 3	109 (36.8)	51 (39.2)		
Skill 4	96 (32.4)	25 (19.2)		
Social media time				
<2 hours	85 (28.7)	32 (24.7)	5.966	0.113
≥2 hours	211 (71.2)	98 (75.4)		
Knowledge of AI Chatbots				
Good	233 (78.7)	115 (88.5)	5.735	**0.017***
Poor	63 (21.3)	15 (11.5)		
Attitude toward AI Chatbot use				
Negative	125 (42.2)	14 (10.8)	40.670	**<0.001***
Positive	171 (57.8)	116 (89.2)		

***Fisher exact**

Table 12 shows the relationship between sociodemographic characteristics and the use of AI chatbots for self-medication. Age was not significantly associated with chatbot use ($\chi^2 = 0.599$, $p = 0.897$), with similar patterns observed across all age groups. There was also no significant association with sex ($\chi^2 = 2.295$, $p = 0.130$), religion ($\chi^2 = 1.417$, $p = 0.234$), marital status ($\chi^2 = 2.445$, $p = 0.118$), ethnic group ($\chi^2 = 2.815$, $p = 0.093$), faculty ($\chi^2 = 0.138$, $p = 0.710$), level of study ($\chi^2 = 5.727$, $p = 0.334$), place of residence ($\chi^2 = 2.544$, $p = 0.111$), monthly allowance ($\chi^2 = 2.519$, $p = 0.641$), guardian education ($\chi^2 = 5.051$, $p = 0.168$), or average time spent on social media ($\chi^2 = 5.966$, $p = 0.113$). However, statistically significant associations were observed for guardian occupation (ILO skill level) ($\chi^2 = 9.941$, $p = 0.019$*), knowledge of AI chatbots ($\chi^2 = 5.735$, $p = 0.017$*), and attitude toward AI chatbot use ($\chi^2 = 40.670$, $p < 0.001$*). Overall, the findings suggest that use of AI chatbots for self-medication is more strongly influenced by knowledge, attitudes, and certain guardian-related socioeconomic factors rather than basic sociodemographic characteristics.

Table 13: Predictors of the use of AI Chatbots for self medication

Variable	B	Odds Ratio	95% C.I.		P-value
			Lower	Upper	
Age (years)					
<18		1			
18-24	-0.642	0.526	0.060	4.617	0.813
25-30	-0.802	0.448	0.054	3.722	
>30	-0.916	0.400	0.046	3.486	
Sex					
Male		1			
Female	0.317	1.373	0.691	2.728	0.365
Religion					
Christianity		1			
Islam		1.882	0.608	5.830	0.273
Marital status					
Single		1			
Married		3.829	0.343	42.789	0.276
Ethnic Group					
Edo indigenes		1			
Non-Edo indigenes	-0.433	0.649	0.403	1.045	0.075
Faculty					
Medical Sciences		1			
Non-Medical Sciences		1.112	0.637	1.940	0.709
Level of study					
Year 1		1			
Year 2		0.741	0.143	3.847	0.961
Year 3		0.943	0.181	4.930	
Year 4		0.663	0.128	3.437	
Year 5		0.779	0.157	3.879	
Year 6		0.929	0.150	5.759	
Place of residence					
On-campus		1			
Off-campus		0.752	0.375	1.508	0.422
Monthly allowance(₦)					
≤50,000		1			
>50,000		0.662	0.325	1.345	0.229
Guardian education					
Primary		1			
Secondary		<0.001	<0.001	<0.001	0.313
Tertiary		1.760	0.541	5.722	
Postgraduate		1.829	0.971	3.445	
Guardian occupation (skill level)					
Skill 1		1			
Skill 2		2.180	0.699	6.797	0.509
Skill 3		0.914	0.417	2.001	
Skill 4		1.134	0.563	2.287	
Knowledge of AI chatbots					
Good		1			
Poor	-0.886	0.413	0.159	1.069	0.068
Attitude toward AI Chatbot Use					
Positive		1			
Negative	-1.728	0.178	0.095	0.330	**<0.001**
Used AI for health info	-2.617	0.073	0.017	0.311	**<0.001**

Nagelkerke Pseudo R^2 =0.253,CI= Confidence Interval,OR= Odds ratio,- reference category*

Table 13 presents the results of the backward logistic regression analysis identifying predictors of the use of AI chatbots for self-medication. Ethnic group was included in the model, with Edo indigenes as the reference category; however, non-Edo indigenes showed no statistically significant association with chatbot use (OR = 0.649, p = 0.075. In contrast, attitude toward AI chatbot use was a strong predictor of behaviour. Participants with a negative attitude were significantly less likely to use AI chatbots for self-medication compared with those with a positive attitude (OR = 0.178, $p < 0.001$). Similarly, respondents who reported using AI for health information also showed a significantly reduced likelihood of using chatbots for self-medication (OR = 0.073, $p < 0.001$). Overall, the final model (Step 13) indicates that attitude-related variables were the strongest predictors of AI chatbot use for self-medication, while sociodemographic factors showed no significant independent influence.

Table 14: Level of Utilization of chatbot use for self-medication

Frequency of chatbot use for self-medication	Frequency	Percentage (%)
Rarely used	108	83.1
Often used	22	16.9
Frequency of device use for health purposes		
Rarely used	70	53.8
Often used	60	46.2
AI chatbots used (self-medication)*		
ChatGPT	140	32.9
Gemini	58	13.6
Google Assistant	23	5.4
Siri	11	2.6
Ada	2	0.5
Woebot	2	0.5
Social media chatbots	8	1.8

*** multiple-response**

Table 14 shows the level of utilization of chatbots for self-medication and related digital health tools among respondents. For chatbot use in self-medication, the majority of respondents reported that they rarely used chatbots (108; 83.1%), while a smaller proportion indicated that they often used them (22; 16.9%). Similarly, for the frequency of device use for health purposes, 70 respondents (53.8%) reported rare use, whereas 60 (46.2%) reported frequent use.

In terms of specific AI chatbots used for self-medication, ChatGPT was the most commonly reported tool (140; 32.9%), followed by Gemini (58; 13.6%) and Google Assistant (23; 5.4%). Fewer respondents reported using Siri (11; 2.6%), social media chatbots (8; 1.8%), Ada (2; 0.5%), and Woebot (2; 0.5%). These percentages reflect multiple-response selections, where respondents could indicate more than one chatbot used.

Table 15: Relationship between Sociodemographic characteristics and Level of Utilization of AI Chatbots (n=130)

Variable	Level of Utilization		Test statistics	p-value
	High	Low		
Age (years)				
<18	10 (23.3)	33 (76.7)	2.110	0.550
18-24	9 (14.1)	55 (85.9)		
25-30	3 (14.3)	18 (85.7)		
>30	0 (0.0)	2 (100.0)		
Sex				
Male	6 (17.6)	28 (82.4)	0.017	0.896
Female	16 (16.7)	80 (83.3)		
Religion				
Christianity	20 (16.1)	104 (83.9)	1.205*	0.268
Islam	2 (33.3)	4 (66.7)		
Marital status				
Single	22 (17.1)	107 (82.9)	0.205*	1.000
Married	0 (0.0)	1 (100.0)		
Ethnic group				
Edo	13 (18.6)	57 (81.4)	0.293	0.588
Non-Edo	9 (15.0)	51 (85.0)		
Faculty				
Medical	11 (23.9)	35 (76.1)	2.474	0.116
Non-medical	11 (13.1)	73 (86.9)		
Level of study				
100	7 (26.9)	19 (73.1)	5.476	0.361
200	6 (19.4)	25 (80.6)		
300	2 (7.1)	26 (92.9)		
400	6 (19.4)	25 (80.6)		
500	0 (0.0)	7 (100.0)		
600	1 (14.3)	6 (85.7)		
Residence				
On-campus	15 (15.0)	85 (85.0)	1.140	0.286
Off-campus	7 (23.3)	23 (76.7)		
Monthly allowance(₦)				
≤50,000	13 (18.8)	56 (81.2)	6.836	0.145
>50,000	9 (14.8)	52 (85.2)		
Guardian education				
Secondary	5 (29.4)	12 (70.6)	2.734	0.255
Tertiary	11 (13.4)	71 (86.6)		
Postgraduate	6 (19.4)	25 (80.6)		
Guardian occupation				
Skill 1	4 (28.6)	10 (71.4)	11.375	**0.010**
Skill 2	11 (28.2)	28 (71.8)		
Skill 3	2 (3.8)	50 (96.2)		
Skill 4	5 (20.0)	20 (80.0)		
Knowledge				
Poor	4 (25.0)	12 (75.0)	0.847*	0.473
Good	18 (15.8)	96 (84.2)		
Attitude				
Poor	5 (33.3)	10 (66.7)	3.248*	0.134
Good	17 (14.8)	98 (85.2)		
Average time spent on social media daily				
<2 hours	6 (18.7)	26 (81.3)	10.577	**0.014**
≥2 hours	16 (16.3)	82 (83.7)		

***Fisher exact**

Table 15 presents the association between socio-demographic variables and the level of utilization of AI chatbots among respondents. Age was not significantly associated with chatbot utilization ($\chi^2 = 2.110$, $p = 0.550$), although slightly higher usage was observed among those aged 16–19 years (23.3%). Similarly, sex showed no significant association ($\chi^2 = 0.017$, $p = 0.896$), with comparable usage between males (17.6%) and females (16.7%). Religion ($\chi^2 = 1.205$, $p = 0.268$), marital status ($\chi^2 = 0.205$, $p = 1.000$), ethnic group ($\chi^2 = 0.293$, $p = 0.588$), faculty ($\chi^2 = 2.474$, $p = 0.116$), level of study ($\chi^2 = 5.476$, $p = 0.361$), residence ($\chi^2 = 1.140$, $p = 0.286$), monthly allowance ($\chi^2 = 6.836$, $p = 0.145$), guardian's education ($\chi^2 = 2.734$, $p = 0.255$), guardian's income ($\chi^2 = 0.763$, $p = 0.858$), knowledge level ($\chi^2 = 0.847$, $p = 0.473$), attitude ($\chi^2 = 3.248$, $p = 0.134$), and use of AI for health information or self-medication ($p = 1.000$ for both) were also not significantly associated with chatbot utilization.

However, a significant association was observed between guardian's occupation and level of chatbot utilization ($\chi^2 = 11.375$, $p = 0.010$), with variation in usage across occupational categories. Social media usage time also showed a significant association ($\chi^2 = 10.577$, $p = 0.014$), indicating that respondents with different daily social media durations differed in their level of chatbot utilization.

Table 16: Predictors of Level of Utilization of AI Chatbots

Variable	B	Odds Ratio	95% CI		P-value
			Lower	Upper	
Age (years)					
<18		1			
18–24	-0.709	0.492	0.017	14.545	0.681
25–30	-0.324	0.723	0.026	20.455	0.849
>30	0.862	2.368	0.068	82.665	0.634
Sex					
Female		1			
Male	1.610	5.000	1.913	13.072	**0.001**
Religion					
Christianity		1			
Islam	-0.277	0.758	0.152	3.778	0.736
Marital Status					
Single		1			
Married	0.562	1.755	0.171	18.058	0.636
Ethnic Group					
Edo indigenes		1			
Non-Edo	-2.998	0.05	0.001	1.705	0.096
Faculty					
Medical Sciences		1			
Non-Medical Sciences	-1.725	0.178	0.023	1.406	0.102
Level of study					
100		1			
200	-20.029	0	0	.	0.999
300	-20.225	0	0	.	0.999
400	-19.906	0	0	.	0.999
500	-19.597	0	0	.	0.999
600	-20.901	0	0	.	0.999
Place of residence					
On-campus		1			
Off-campus	-0.197	0.822	0.303	2.226	0.699
Guardian's Occupation (ILO)					
Skill 1		1			
Skill 2	1.580	4.854	0.596	39.511	0.140
Skill 3	-0.447	0.639	0.094	4.351	0.648
Skill 4	-3.069	0.046	0.005	0.404	**0.005**
Monthly allowance					
≤50,000		1			
>50,000	0.245	1.277	0.201	8.119	0.795
Average time spent on social media daily					
<2 hours		1			
≥2 hours	1.386	4.000	0.895	17.872	0.070

*Nagelkerke Pseudo R^2 = 0.253, CI= Confidence Interval, OR= Odds ratio, *- reference category*

Table 16 presents the multivariate logistic regression analysis of factors associated with the outcome variable. Regarding guardian's occupation (ILO classification), compared to the reference category (Skill 1), Skill 2 showed increased odds of the outcome (OR = 4.854; 95% CI: 0.596–39.511), though this was not statistically significant ($p = 0.140$). Skill 3 showed reduced odds (OR = 0.639; 95% CI: 0.094–4.351; $p = 0.648$), while Skill 4 was significantly associated with lower odds of the outcome (OR = 0.046; 95% CI: 0.005–0.404; $p = 0.005$).

Monthly allowance was not a significant predictor across all categories when compared with the reference group (<10,000), although a non-significant reduction in odds was observed for the 31,000–50,000 category (OR ≈ 0.000; $p = 0.998$). Similarly, average time spent on social media per day showed no statistically significant associations, although respondents using social media for ≥2 hours daily had higher odds of the outcome (OR = 4.000; 95% CI: 0.895–17.872; $p = 0.070$) compared to those using it for <2 hours.

Overall, only Skill 4 under guardian occupation were statistically significant predictors of the outcome at $p < 0.05$, while other variables showed no significant independent effect.

SECTION E: PERCEIVED RISKS AND INFLUENCING FACTORS

Table 17: Perceived Risks and Influencing Factors

Item	Frequency (%)		
	Disagree	Neutral	Agree
Chatbots may cause drug misuse	38 (8.9)	41 (9.6)	343 (80.5)
Guidelines needed for health chatbots	22 (5.2)	28 (6.6)	372 (87.3)
Peer pressure affects chatbot use	52 (12.2)	60 (14.1)	310 (72.8)
Internet access impacts chatbot use	51 (12.0)	62 (14.6)	309 (72.5)

Regarding perceived risks and influencing factors related to AI chatbot use for self-medication, a substantial majority of respondents expressed concerns about potential harms and acknowledged social and practical influences. Specifically, 80.5% agreed that chatbots may cause drug misuse, while only 8.9% disagreed. An overwhelming 87.3% agreed that guidelines are needed for health chatbots, with just 5.2% disagreeing. Peer pressure was recognized as a factor by 72.8% of participants, and a similar proportion (72.8%) agreed that friends' use increases their own chatbot use. Additionally, 72.5% agreed that internet access impacts chatbot use. Neutral responses were consistently low across all items, ranging from 6.6% to 14.6%, indicating strong and clear perceptions among the vast majority of participants (Table 14).

Table 18: Perceived Risks & Influences of AI Chatbots

Item	Present Frequency (%)	Absent Frequency (%)
Chatbots may cause drug misuse	343 (80.5)	83 (19.5)
Guidelines needed for health chatbots	372 (87.3)	54 (12.7)
Peer pressure affects chatbot use	310 (72.8)	116 (27.2)
Internet access impacts chatbot use	309 (72.5)	117 (27.5)

Cronbach's Alpha: 0.799

Table 15 shows respondents' appropriateness of responses regarding perceived risks and influences of AI chatbot use. A large majority appropriately agreed that chatbots may cause drug misuse (343, 80.5%), while only a small proportion responded inappropriately (83, 19.5%). Similarly, most respondents appropriately supported the need for guidelines on health chatbots (372, 87.3%), with few inappropriate responses (54, 12.7%).

For social and environmental influences, a high proportion appropriately acknowledged that peer pressure affects chatbot use (310, 72.8%), internet access impacts usage (309, 72.5%), and friends' use increases chatbot adoption (310, 72.8%), while the remaining respondents gave inappropriate responses (116, 27.2%; 117, 27.5%; and 116, 27.2% respectively). Overall, the scale demonstrated good internal consistency, with a Cronbach's alpha of 0.799.

Table 19: Predictors of the factors influencing the use of AI Chatbots for self medication

Variable	B	Odds ratio	95% CI		P-value
			Lower	Upper	
Chatbots may cause drug misuse	0.066	1.068	0.483	2.363	0.871
Guidelines needed for health chatbots	-0.598	0.55	0.204	1.486	0.238
Peer pressure affects chatbot use	-0.197	0.821	0.386	1.747	0.609
Internet access impacts chatbot use	0.53	1.699	0.818	3.532	0.155

Table 19 presents the predictors of factors influencing the use of AI chatbots for self-medication. The logistic regression analysis revealed that most perceived risks and influencing factors were not statistically significant. Specifically, the beliefs that chatbots may cause drug misuse ($B = 0.066$, $p = 0.871$), that guidelines are needed for health chatbots ($B = -0.598$, $p = 0.238$), that peer pressure affects chatbot use ($B = -0.197$, $p = 0.609$), and that internet access impacts chatbot use ($B = 0.530$, $p = 0.155$) all failed to reach statistical significance. However, the influence of friends' use was a significant predictor ($B = -0.848$, $p = 0.018$, $Exp(B) = 0.428$, 95% CI: 0.212–0.864), indicating that participants whose friends used chatbots were approximately 57% less likely to engage in self-medication compared to those whose friends did not use chatbots. The variable assessing the need to educate students on safe chatbot use could not be reliably interpreted due to an extremely large standard error (S.E. = 11945.25), resulting in a non-significant but unstable estimate ($p = 0.999$). The constant term was not significant ($B = 0.119$, $p = 0.798$). Overall, the model suggests that while most concerns about risks and external factors do not independently predict AI chatbot use for self-medication, the behaviour of friends plays a notable and protective role.

Table 20: Recommendation and negative implications of AI chatbots for self medication

Variable	Frequency	Percentage (%)
Students should be educated on safe use of AI chatbots		
Yes	411	96.5
No	11	2.6
Possible negative implications of using AI chatbots*		
Wrong diagnosis	372	87.3
Incorrect dosage	333	78.2
Adverse drug reaction	263	61.7
Drug interactions	197	46.2
Delay in seeking care	284	66.7
Drug resistance	205	48.1

*** multiple response**

Table 17 shows that the vast majority of students (96.5%) believe that education on the safe use of AI chatbots is necessary. Regarding potential negative implications of using AI chatbots for self-medication, respondents identified several risks: wrong diagnosis (87.3%), incorrect dosage (78.2%), adverse drug reactions (61.7%), delay in seeking care (66.7%), drug interactions (46.2%), and drug resistance (48.1%).

CHAPTER FIVE

DISCUSSION, CONCLUSION AND RECOMMENDATION

5.1 DISCUSSION

The sociodemographic profile of respondents in this study reflects a predominantly young undergraduate population, with just over half of respondents aged 18–24 years. This pattern is consistent with previous studies among university students in Ekiti state where the majority fall within the 18–25-year age group [21,18]. This age group represents digital natives who are more likely to adopt emerging technologies such as AI chatbots, thereby influencing health-seeking behaviors, including self-medication.

The predominance of female respondents, accounting for about four-fifths of the study population, compared to about one-fifth males, aligns with findings from Nigerian studies where females constituted the majority [19,18]. Gender differences in health information-seeking behavior have been widely reported, with females generally more likely to engage with health resources, including digital platforms, which may increase their use of AI chatbots for health-related decisions.

In terms of religion, over nine-tenths of respondents were Christians, while less than one-tenth were Muslims. This reflects the religious distribution in Southern Nigeria and is consistent with findings from similar local studies [21]. Although religion may not directly influence AI chatbot use, it can shape health beliefs and attitudes toward practices such as self-medication.

The overwhelming majority of respondents were single, accounting for more than nine-tenth of the study population, with only about one-tenth being married. This is consistent with findings from undergraduate-based studies in Arab countries where most participants are unmarried due to their life stage [18]. This demographic may reflect greater independence in making personal health decisions.

Ethnically, approximately three-fifths of respondents were Edo indigenes, while about two-fifths were from other ethnic groups. This diversity mirrors the heterogeneous composition of Nigerian universities. Cultural background has been shown to influence health beliefs and may indirectly affect acceptance of AI chatbots [15].

Regarding academic background, about one-third of respondents were in medical sciences, while roughly two-thirds were from non-medical faculties. This is important, as studies in Nigeria and Malaysia have shown that medical students tend to have higher knowledge and are more critical of AI-generated health information compared to non-medical students [20,17]. In contrast, non-medical students may rely more on easily accessible tools such as AI chatbots due to limited formal health education.

The distribution across levels of study showed that about one-quarter were in 100 level, smaller proportions in 500 and 600 levels, one in sixteen and about one in thirty, respectively. Similar patterns have been observed in other studies [17,26], although higher-level students are generally more exposed to AI tools and may demonstrate greater confidence in their use [20,26].

Most respondents resided on campus, accounting for just over four-fifths, while less than one-fifth lived off campus. Access to stable internet and peer influence in campus settings has been identified as a key factor influencing the adoption of digital technologies, including AI chatbots [15,25].

Guardian education revealed that about three-fifths had tertiary education and over one-quarter had postgraduate education, with only a small minority about one-tenth having secondary or primary education. Higher guardian education has been associated with improved health literacy and greater exposure to digital tools [20]. Socioeconomic classification further showed that about one-half of respondents belonged to the middle class, over one-third to the high class, and about one-eighth to the low class. These findings are consistent with studies indicating that socioeconomic status significantly influences both health behavior and technology adoption [25,17].

The predominance of young, digitally active students in University of Benin suggests a high likelihood of widespread reliance on AI chatbots for health information, creating both opportunities and risks. While these tools can improve access to health knowledge, concerns arise around misinformation, inappropriate self-medication, and delayed healthcare seeking. The large proportion of non-medical students further indicates potential gaps in health literacy, increasing the likelihood of uncritical reliance on AI-generated advice. In addition, observed socioeconomic disparities imply that some students may turn to AI chatbots as a cost-effective alternative to professional healthcare, which, although improving accessibility, may heighten the risk of misuse if information is inaccurate or misunderstood. However, the high number of students residing on campus provides a strategic opportunity for institution-based interventions, positioning the university as an effective platform for targeted digital health education and health promotion programs aimed at encouraging the safe and informed use of AI tools.

In this study, all respondents had heard of AI chatbots and about four-fifth of respondents demonstrated good knowledge. This finding differs from a previous study conducted among healthcare students in the Americas which reported a minimal self-reported knowledge level.[14] The difference may be due to the global surge in AI visibility and media coverage between the timing of that earlier study and the present one. The high awareness observed in this study aligns more closely with a Nigerian study among pharmacy students where familiarity with AI chatbots was also high.[19] The main sources of knowledge in this study were the internet and social media, which supports findings from another Nigerian study where students primarily learned about AI through social media platforms rather than formal education.[24]

Regarding specific chatbot recognition, Gemini was the most correctly identified tool in this study, with a higher recognition rate than ChatGPT. This finding contrasts with earlier Nigerian studies where ChatGPT was the most commonly known and used tool among pharmacy and medical students.[19,20] The prominence of Gemini in this population may reflect recent marketing shifts, pre-installation on certain mobile devices, or integration with commonly used Google services among students in this setting. Despite high awareness, only a small fraction of respondents had received formal training on AI or chatbots. This gap between awareness and formal training mirrors findings from a study at Abia State University where awareness was high but formal training was low.[22] The low level of formal training in this study is similar to the findings from a study done in Obafemi Awolowo University that students often overestimate their objective knowledge of AI despite lacking structured education on the topic.[26]

The study found that male students were significantly more likely to have good knowledge of AI chatbots than female students. This gender disparity is consistent with a previous Nigerian study which reported that male medical students were more likely to use ChatGPT and demonstrated more positive tendencies toward the technology.[20] Another study among Nigerian health students also noted that males and older students had higher odds of using ChatGPT.[20] The reasons for this gender gap are not entirely clear but may relate to differential access to technology, differing peer influences, or variations in confidence with digital tools.

Guardian occupation also emerged as a predictor of knowledge in this study. Students whose guardians were in higher skill occupations demonstrated better knowledge. This finding aligns with research from Arab countries where the type of university and academic background of guardians played a significant role in chatbot adoption and familiarity.[27] It suggests that socioeconomic and educational capital at home may translate into greater digital literacy and exposure to emerging technologies like AI.

The high level of awareness and generally good knowledge suggests that AI tools are already a major source of health information, particularly through informal channels such as the internet and social media. However, the low level of formal training indicates a critical gap, raising concerns about misinformation, misuse, and overconfidence in unverified knowledge. Observed disparities by gender and socioeconomic background further suggest unequal access to digital literacy, which may widen health information inequalities. The prominence of newer tools like Gemini also reflects the rapidly evolving nature of digital health platforms, emphasizing the need for continuous monitoring and adaptation of health education strategies. Overall, these findings underscore the need for structured digital health literacy programs, integration of AI education into academic curricula, and targeted interventions to ensure safe, equitable, and informed use of AI chatbots in health decision-making.

The attitude of respondents in this study, with about seven-tenth of respondents expressing a positive attitude but also showing significant caution about reliability and safety. While many respondents agreed that AI chatbots help in understanding drug dosage and instructions and that using them saves time and money, a larger proportion disagreed that chatbots provide reliable information for self-medication. This finding is consistent with a large multinational study from the Arab world which reported that while some students adopted chatbots for self-medication, others were afraid of issues regarding accuracy and reliability.[18]

The strong agreement in this study that AI chatbots should not replace healthcare professionals aligns with findings from a Nigerian survey of medical students and faculty. [24] In that study, respondents were open to using AI for learning and self-medication but feared that the technology could dehumanize healthcare services and reduce the skills of physicians.[24] Similarly, a study at Ekiti State University noted that while students had no objection to using medical chatbots, they feared the health advice offered would be inaccurate and unreliable.[21] The present study confirms that these concerns persist among students in Benin City. About seven-tenth of respondents appropriately recognized the risks of inappropriate drug use and the negative health effects of relying on chatbots. This concerns of drawbacks was also reported in a Zambian study where low perceived risk was a key factor associated with positive attitudes toward AI chatbots.[23] In the Zambian context, [23] students with low anxiety and high social influence had more favourable views, which suggests that the cautious attitudes observed in Benin City may be protective in a setting where guidelines for AI use are not yet established.

This study found that knowledge of AI chatbots was significantly associated with attitude. Respondents with good knowledge demonstrated more positive attitudes compared to those with poor knowledge. This finding is consistent with research from the Americas which concluded that perceived knowledge and positive ethical perceptions had a strong relationship with positive attitudes towards ChatGPT.[14] It also supports the findings from a Malaysian study where higher knowledge and positive attitudes were highly related.[17]

Guardian occupation was a consistent predictor of attitude in this study. Students whose guardians were in skill level 3 and 4 showed more positive attitudes. This mirrors the trend observed with knowledge and reinforces the idea that family background influences a student's openness to new health technologies. A study in Arab countries also found that socio-demographic and academic variables such as age and country of residence played a significant role in shaping attitudes toward chatbot adoption.[27] The absence of a significant association between faculty type and attitude in this study differs from some previous research. A Malaysian study found that MBBS students were more likely to use ChatGPT than students of dentistry and allied health sciences.[17] The lack of difference between medical and non-medical students in Benin City may indicate that the perceived utility of AI for health information is universal across disciplines or that the baseline awareness is high enough across all faculties to equalize attitudes.

The findings from this study carry important public health implications regarding the adoption of AI chatbots for health-related purposes. Although a majority of respondents expressed a generally positive attitude toward AI chatbots, recognizing their usefulness in saving time, cost, and aiding understanding of medication instructions, there was a strong and appropriate caution about their reliability and safety. This balanced perception is beneficial from a public health perspective, as it may reduce the risk of harmful practices such as self-medication based solely on AI-generated advice. The widespread agreement that AI chatbots should not replace healthcare professionals further reinforces the continued importance of formal healthcare systems. The association between better knowledge and more positive attitudes suggests that improving digital health literacy could promote safer and more effective use of AI tools. Additionally, the influence of socioeconomic background on attitudes highlights potential inequalities in the adoption and use of digital health technologies. Overall, these findings underscore the need for targeted health education, clear guidelines on AI use in healthcare, and policies that ensure safe, equitable, and informed engagement with emerging digital health tools.

The prevalence of AI chatbot use for self-medication in this study was notable, with nearly one third of respondents having used chatbots for this purpose. This finding is higher than the usage reported in a large Arab world study where only about a quarter of participants utilized chatbots for health coaching, self-diagnosis, or self-medication.[18] The higher prevalence in this study may be due to the specific demographic of university students who are heavy mobile device users and early adopters of digital tools. The finding that all respondents owned a mobile device and nearly all used AI chatbots for some purpose provides a fertile ground for the adoption of these tools for health-related activities.

The pattern of use in this study showed that ChatGPT was the most commonly used chatbot for self-medication, followed by Gemini. This aligns with the global and Nigerian literature where ChatGPT is consistently the most utilized AI tool among students.[19,20,91] A study in Uganda also reported that ChatGPT was the most popular AI tool among medical students, with students using it for both academic and personal health-related applications.[91] The conditions most frequently addressed using AI chatbots in this study included skin conditions, menstrual pain, and stomach upset. These are common ailments that students might feel are minor enough to manage without visiting a health facility. This aligns with the context provided by a Nigerian community-based survey which found that headaches, febrile illnesses, and body pains were the most common reasons for self-medication.[13] The availability of AI chatbots may now provide a new avenue for students to seek medical advice on these familiar complaints.

Despite the prevalence of use, the frequency of chatbot utilization for self-medication was mostly occasional or rare. The majority of users did not use chatbots very often for this purpose. This pattern of selective use mirrors the findings from a Malaysian study where the majority of students were selective users of ChatGPT, utilizing the system to support certain aspects of their work but not relying on it entirely.[17] The low frequency of use may be a reflection of the cautious attitudes identified in this study. Students are trying the technology but are not yet integrating it fully into their health decision-making.

The study found that knowledge and attitude were significantly associated with the use of AI chatbots for self-medication. Respondents with good knowledge and those who had used AI for health information were more likely to use chatbots for self-medication. This is consistent with the Technology Acceptance Model and findings from studies in the United States and China which show that perceived usefulness and social influence drive adoption.[25,16] The regression analysis revealed a negative attitude was associated with lower odds of actual use. This suggests that students who lack a favourable view of AI are also more aware of its limitations and therefore may be more restrained in applying it for self-medication. This cautious approach is supported by the finding that a majority of users in an American study were doubtful about the output of ChatGPT and required physician assurances.[90]

This study found that basic sociodemographic characteristics such as age, sex, level of study, and faculty were not significant predictors of using AI chatbots for self-medication. This is contrary to a study among Nigerian medical and dental students which found that males and older students were more likely to use ChatGPT.[20] A Chinese study also identified personal characteristics and environmental backgrounds as significant in dictating the usage of chatbots.[16] The lack of association in this study cohort may indicate that AI chatbot use for health is becoming more democratized among university students, cutting across traditional demographic lines. The high penetration of smartphones and internet access among this population likely reduces barriers that might otherwise create disparities.

Guardian occupation did emerge as a factor associated with the level of utilization, which is consistent with the earlier findings on knowledge and attitude. Students from homes with higher occupational skill levels may have greater exposure to technology and more resources to explore digital health tools. A study in Arab countries also identified the type of university and recent academic performance of guardians as significant factors, suggesting that the academic and social environment plays a role.[27]

The finding that the average time spent on social media was associated with the level of utilization is also important. Students who spend more time online are naturally more exposed to information about AI tools and may be more comfortable integrating them into various aspects of their lives, including health. This aligns with research from the United States where younger age and lower educational attainment were associated with higher use of ChatGPT for health information, indicating a demographic that is digitally native and comfortable seeking information online.[90]

Finally, the overwhelming support for education on the safe use of AI chatbots for self-medication highlights an important need identified by the students themselves. This finding is in line with the call from previous Nigerian studies for formal AI education to be included in the educational curriculum.[19,20] The concerns about wrong diagnosis, incorrect dosage, and delay in seeking care indicate that students are not naive users. They recognize the potential for harm and are seeking guidance on how to navigate this new landscape responsibly. The findings from this study provide a strong rationale for Nigerian universities to develop clear policies and educational programs on the appropriate use of AI chatbots for health information.

5.2 Conclusion

All respondents had heard of AI chatbots, with Gemini serving as the most identified tool in the study. About four-fifth of respondents demonstrated good knowledge of AI chatbots. Guardian occupation also emerged as a predictor of knowledge in this study. Students whose guardians were in higher skill occupations demonstrated better knowledge.

About seven-tenth of respondents expressed a positive attitude towards use of AI chatbot for self medication but also showed significant caution about reliability and safety. Good knowledge and guardians occupation were significant predictors, showing more positive attitude.

The prevalence of AI chatbot use for self-medication in this study was about one third of respondents having used chatbots for this purpose. The pattern of use in this study showed that ChatGPT was the most commonly used chatbot for self-medication.

Knowledge, attitude, guardians occupation and average time spent on social media were significant factors influencing use of AI chatbots for self medication, with good knowledge, guardians occupation of higher skill level and students who spent more time on social media, more likely to use AI chtatbots for self medication.

5.3 Recommendations

To the Government

1. The Federal Ministry of Health and Social Welfare and the Ministry of Communications and Digital Economy must work together to create a national framework of the regulation and ethical use of AI chatbots in healthcare. This framework ought to set down a clear guideline to health-related AI applications that safeguard consumers against misinformation and possible harm.
2. Awareness regarding the dangers of self-medication with the help of unverified AI tools and digital health literacy of young adults should be raised via public health campaigns.

To University Administration

1. University leaders, especially in Benin City, ought to incorporate digital health literacy and AI ethics in the general studies program of all undergraduate students.
2. The institution should conduct regular workshops and seminars to train students on how to utilize AI chatbots to academic and health benefits.
3. The use of AI tools to do assignments and health-related inquiries should be presented clearly as institutional policies and communicated to the student body.

To students

1. Undergraduate students must be cautious when using AI chatbots with health advice and must always consult qualified healthcare professionals before using any medication.
2. There are online courses and institutional workshops that should be exploited by students in order to get a better idea of the potential as well as the weaknesses of AI tools.

3. Responsible AI chatbot use can be encouraged by utilizing peer education among other students, that such tools are intended to complement and not replace medical care.

REFERENCES

1. Gignac GE, Szodorai ET. Defining intelligence: Bridging the gap between human and artificial perspectives. *Intelligence*. 2024;104:101832.
2. Ahmad SF, Han H, Alam MM, Rehmat MK, Irshad M, Arraño-Muñoz M, Ariza-Montes A. Impact of artificial intelligence on human loss in decision making, laziness and safety in education. *Humanities and Social Sciences Communications*. 2023;10(1):311.
3. De La Roca M, Chan MM, Garcia-Cabot A, Garcia-Lopez E, Amado-Salvatierra H. The impact of a chatbot working as an assistant in a course for supporting student learning and engagement. *Computer Applications in Engineering Education*. 2024;32(5):e22750.
4. Khosravi M, Zare Z, Mojtabaeian SM, Izadi R. Artificial intelligence and decision-making in healthcare: A thematic analysis of a systematic review of reviews. *Health Services Research and Managerial Epidemiology*. 2024;11:23333928241234863.
5. Faiyazuddin M, Rahman SJQ, Anand G, Siddiqui RK, Mehta R, Khatib MN, Gaidhane S, Zahiruddin QS, Hussain A, Sah R. The impact of artificial intelligence on healthcare: A comprehensive review of advancements in diagnostics, treatment, and operational efficiency. *Health Science Reports*. 2025;8(1):e70312.
6. Amin R, Darwin R, Dey BK, Dhama K, Bin Emran T. Examining the differences between how doctors and artificial intelligence chatbots handle patient symptoms. *International Journal of Surgery*. 2023;109(10):2892–2895.
7. Baracaldo-Santamaría D, Trujillo-Moreno MJ, Pérez-Acosta AM, Feliciano-Alfonso JE, Calderon-Ospina CA, Soler F. Definition of self-medication: A scoping review. *Therapeutic Advances in Drug Safety*. 2022;13:20420986221127501.
8. Alomoush A, Alkhawaldeh A, ALBashtawy M, Hamaideh S, Ta'an W, Abdelkader R, Mohammad K, Rayan A, Alsadi M, Khraisat O, Shyab M, Al-Amer R, Suliman M, Ayed A, Abdalrahim A, Al-Qudah M. Self-medication and its associated factors among university students: A cross-sectional study. *Iranian Journal of Nursing and Midwifery Research*. 2024;29(2):268–271.
9. Olagunju OJ, Ben E, Olagunju O, Majolagbe OG, Osanyinlusi OO, Adewoye T, Atoyebi OF, Ojo IO, Dawha SD. Poorly regulated antibiotic use in Nigeria: A critical public health concern and its impact on medical practice. *Cureus*. 2025;17(6):e85212.
10. Aggarwal A, Tam CC, Wu D, Li X, Qiao S. Artificial intelligence-based chatbots for promoting health behavioral changes: Systematic review. *Journal of Medical Internet Research*. 2023;25:e40789.
11. Habiba U, Koli FS. The mediating role of students' health information literacy skills: Exploring the relationship between web resource utilization and health information evaluation proficiency. *Health Expectations*. 2024;27(4):e14176.
12. Barreda M, Cantarero-Prieto D, Coca D, Delgado A, Lanza-León P, Lera J, Montalbán R, Pérez F. Transforming healthcare with chatbots: Uses and applications—A scoping review. *Digital Health*. 2025;11:20552076251319174.

13. Bassi PU, Osakwe AI, Builders M, Ette Ettebong K, Kola G, Binga B, Oreagbai I. Prevalence and determinants of self-medication practices among Nigerians. *African Journal of Health Sciences*. 2021;34(5):634–649.
14. Cherrez-Ojeda I, Gallardo-Bastidas JC, Robles-Velasco K, Osorio MF, Velez Leon EM, Leon Velastegui M, Pauletto P, Aguilar-Díaz FC, Squassi A, González Eras SP, Cordero Carrasco E, Chavez Gonzalez KL, Calderon JC, Bousquet J, Bedbrook A, Faytong-Haro M. Understanding health care students' perceptions, beliefs, and attitudes toward AI-powered language models: cross-sectional study. *JMIR Medical Education*. 2024;10:e51757.
15. Zheng A, Long L, Govathson C, Chetty Makkan C, Morris S, Rech D, Fox MP, Pascoe S. Designing artificial intelligence powered health care assistants to reach vulnerable populations: a discrete choice experiment among South African university students. *Mayo Clinic Proceedings: Digital Health*. 2025;3(3):100248.
16. Tao W, Yang J, Qu X. Utilization of, perceptions on, and intention to use AI chatbots among medical students in China: national cross-sectional study. *JMIR Medical Education*. 2024;10:e57132.
17. Pallivathukal RG, Kyaw Soe HH, Donald PM, Samson RS, Hj Ismail AR. ChatGPT for academic purposes: survey among undergraduate healthcare students in Malaysia. *Cureus*. 2024;16(1):e53032.
18. Abdelwahed AE, Abd El-Nasser M, Heih OQ, Suleiman AM, Khader AM, Ibrahim RA, Fathalla Hamad MRA, Radwan E, Srour AM, HealthTech Alliance, Ghallab MMI. Public attitudes and practices toward using AI chatbots for healthcare assistance: a multinational cross-sectional study. *BMC Health Services Research*. 2025;25:in press.
19. Orok E, Okaramee C, Egboro B, Egbochukwu E, Bello K, Etukudo S, Ogologo MS, Onyeka P, Etukokwu O, Kolawole M, Orire A, Ekada I, Akawa O. Pharmacy students' perception and knowledge of chat-based artificial intelligence tools at a Nigerian university. *BMC Medical Education*. 2024;24:1237.
20. Iliyasu Z, Abdullahi HO, Iliyasu BZ, Bashir HA, Amole TG, Abdullahi HM, Abdullahi AU, Kwaku AA, Dahir T, Tsiga-Ahmed FI, Jibo AM, Salihu HM, Aliyu MH. Correlates of medical and allied health students' engagement with generative AI in Nigeria. *Medical Science Educator*. 2024;35(1):269–280.
21. Aina MA, Gbenga-Epebinu MA, Olofinbiyi RO, Ogidan OC, Ayedun TO. Perception and acceptance of medical chatbot among undergraduates in Ekiti State University, Nigeria. *British Journal of Education*. 2023;11(11):1–14.
22. Muoka CG, Ewurum O, Godwin GU, Nwoke-Udeka I, Nnedimma AV, Moneke I. Assessment of knowledge, attitudes, perceptions, and utilization of artificial intelligence in medical education among medical students in a Nigerian university. *International Journal of Research in Medical Sciences*. 2025;13(6):2309–2320.
23. Mudenda S, Mufwambi W, Mwale RS, Kathewera B, Lubanga AF. Attitudes and usage of ChatGPT among pharmacy students in a sub-Saharan African country, Zambia: findings and implications on the education system. *BMC Medical Education*. 2025;25(1):1237.

24. Oluwadiya KS, Adeoti AO, Agodirin SO, Nottidge TE, Usman MI, Gali MB, Onyemaechi NO, Ramat AM, Adedire A, Zakari LY. Exploring artificial intelligence in the Nigerian medical educational space: an online cross-sectional study of perceptions, risks and benefits among students and lecturers from ten universities. *Nigerian Postgraduate Medical Journal*. 2023;30(4):285–292.
25. Pham L, Klaus T, Bateh J. Key factors influencing intention to use ChatGPT: an empirical study of U.S. students. *Acta Psychologica*. 2025;260:105516.
26. David-Olawade AC, Wada OZ, Adeniji YJ, Aderupoko IV, Olawade DB. Artificial intelligence readiness among healthcare students in Nigeria: a cross-sectional study assessing knowledge gaps, exposure, and adoption willingness. *International Journal of Medical Informatics*. 2025;204:106085.
27. Abdaljaleel M, Barakat M, Alsanafi M, Salim NA, Abazid H, Malaeb D, Mohammed AH, Hassan BAR, Wayyes AM, Farhan SS, Khatib SE, Rahal M, Sahban A, Abdelaziz DH, Mansour NO, AlZayer R, Khalil R, Fekih-Romdhane F, Hallit R, Hallit S, Sallam M. A multinational study on the factors influencing university students' attitudes and usage of ChatGPT. *Scientific Reports*. 2024;14(1):1983.
28. -Watters C, Lemanski MK. Universal skepticism of ChatGPT: A review of early literature on chat generative pre-trained transformer. *Frontiers in Big Data*. 2023;6:1224976.
29. Gao S, He L, Chen Y, Li D, Lai K. Public perception of artificial intelligence in medical care: Content analysis of social media. *Journal of Medical Internet Research*. 2020;22:e16649.
30. Kocaballi AB, Berkovsky S, Quiroz JC, Laranjo L, Tong HL, Rezazadegan D, Briatore A, Coiera E. The personalization of conversational agents in health care: Systematic review. *Journal of Medical Internet Research*. 2019;21:e15360.
31. Nadarzynski T, Miles O, Cowie A, Ridge D. Acceptability of artificial intelligence (AI)-led chatbot services in healthcare: A mixed-methods study. *Digital Health*. 2019;5:2055207619871808.
32. De Duro ES, Improta R, Stella M. Introducing CounseLLMe: A dataset of simulated mental health dialogues for comparing LLMs like Haiku, LLaMAntino and ChatGPT against humans. *Emerging Trends in Drugs, Addictions, and Health*. 2024;5:100170.
33. Devine D, Gaskell J, Jennings W, Stoker G. Trust and the coronavirus pandemic: What are the consequences of and for trust? An early review of the literature. *Political Studies Review*. 2021;19:274–285.
34. Stella M, Hills TT, Kenett YN. Using cognitive psychology to understand GPT-like models needs to extend beyond human biases. *Proceedings of the National Academy of Sciences of the United States of America*. 2023;120:e2312911120.
35. Metze K, Morandin-Reis RC, Lorand-Metze I, Florindo JB. Bibliographic research with ChatGPT may be misleading: The problem of hallucination. *Journal of Pediatric Surgery*. 2024;59:158.
36. Pugliese N, Wong VWS, Schattenberg JM, Romero-Gomez M, Sebastiani G, Castera L, Hassan C, Manousou P, Miele L, Peck R. Accuracy, reliability, and comprehensibility of

ChatGPT-generated medical responses for patients with nonalcoholic fatty liver disease. *Clinical Gastroenterology and Hepatology*. 2024;22:886–889.
37. Dixit S, Kumar A, Srinivasan K, Vincent P, Krishnan NR. Advancing genome editing with artificial intelligence: Opportunities, challenges, and future directions. *Frontiers in Bioengineering and Biotechnology*. 2024;12:1335901.
38. Liu Y, Zhang T, You N, Wu S, Shen N. MAGPIE: Accurate pathogenic prediction for multiple variant types using machine learning approaches for functional characterization of genetic variants. *Genome Medicine*. 2024;16:3.
39. Jumper J, Evans R, Pritzel A, Green T, Figurnov M, Ronneberger O, Tunyasuvunakool K, Bates R, Žídek A, Potapenko A. Highly accurate protein structure prediction with AlphaFold. *Nature*. 2021;596:583–589.
40. Frasca M, La Torre D, Repetto M, De Nicolò V, Pravettoni G, Cutica I. Artificial intelligence applications to genomic data in cancer research: A review of recent trends and emerging areas. *Discovery Analytics*. 2024;2:10.
41. Qureshi R, Irfan M, Gondal T, Khan S, Wu J, Hadi M, Heymach J, Le X, Yan H, Alam T. AI in drug discovery and its clinical relevance. *Heliyon*. 2023;9:e17575.
42. Miner AS, Milstein A, Hancock JT, Johnson K, Choi E, Kaplin S, Venner E, Murugan M, Wang Z, Glicksberg B. Artificial intelligence and cardiovascular genetics. *Life*. 2022;12:279.
43. Abe S, Tago S, Yokoyama K, Ogawa M, Takei T, Imoto S, Fuji M. Explainable AI for estimating pathogenicity of genetic variants using large-scale knowledge graphs. *Cancers*. 2023;15:1118.
44. Al-Hilli Z, Noss R, Dickard J, Wei W, Chichura A, Wu V, Renicker K, Pederson H, Eng C. A randomized trial comparing the effectiveness of pre-test genetic counseling using an artificial intelligence automated chatbot and traditional in-person genetic counseling in women newly diagnosed with breast cancer. *Annals of Surgical Oncology*. 2023;30:5990–5996.
45. Floris M, Moschella A, Alcalay M, Montella A, Tirelli M, Fontana L, Idda M. Pharmacogenetics in Italy: Current landscape and future prospects. *Human Genomics*. 2024;18:78.
46. Idda M, Zoledziewska M, Urru S, McInnes G, Bilotta A, Nuvoli V, Lodde V, Orrù S, Schlessinger D, Cucca F. Genetic variation among pharmacogenes in the Sardinian population. *International Journal of Molecular Sciences*. 2022;23:10058.
47. Chakraborty C, Pal S, Bhattacharya M, Dash S, Lee S. Overview of chatbots with special emphasis on artificial intelligence-enabled ChatGPT in medical science. *Frontiers in Artificial Intelligence*. 2023;6:1237704.
48. Jeyaraman M, Balaji S, Jeyaraman N, Yadav S. Unraveling the ethical enigma: Artificial intelligence in healthcare. *Cureus*. 2023;15:e43262.
49. Yang T, White M, Lipson-Smith R, Shannon MM, Latifi M. Design decision support for healthcare architecture: A VR-integrated approach for measuring user perception. *Buildings*. 2024;14:797.

50. Junaid SB, Imam AA, Balogun AO, De Silva LC, Surakat YA, Kumar G, Abdulkarim M, Shuaibu AN, Garba A, Sahalu Y. Recent advancements in emerging technologies for healthcare management systems: A survey. *Healthcare*. 2022;10:1940.
51. Cheng K, He Y, Li C, Xie R, Lu Y, Gu S, Wu H. Talk with ChatGPT about the outbreak of Mpox in 2022: Reflections and suggestions from AI dimensions. *Annals of Biomedical Engineering*. 2023;51:870–874.
52. Wang CW, Hsu BY, Chen DY. Chatbot applications in government frontline services: Leveraging artificial intelligence and data governance to reduce problems and increase effectiveness. *Asia Pacific Journal of Public Administration*. 2024;46:488–511.
53. Chakraborty S, Paul H, Ghatak S, Pandey SK, Kumar A, Singh KU, Shah MA. An AI-based medical chatbot model for infectious disease prediction. *IEEE Access*. 2022;10:128469–128483.
54. Bender EM, Gebru T, McMillan-Major A, Shmitchell S. On the dangers of stochastic parrots: Can language models be too big? In: *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*. Virtual Event; 2021 Mar 3–10. p. 610–623.
55. Krishnan G, Singh S, Pathania M, Gosavi S, Abhishek S, Parchani A, Dhar M. Artificial intelligence in clinical medicine: Catalyzing a sustainable global healthcare paradigm. *Frontiers in Artificial Intelligence*. 2023;6:1227091.
56. Singh J, Sillerud B, Singh A. Artificial intelligence, chatbots and ChatGPT in healthcare: Narrative review of historical evolution, current application, and change management approach to increase adoption. *Journal of Medical Artificial Intelligence*. 2023;6:30.
57. Babu A, Boddu SB. BERT-based medical chatbot: Enhancing healthcare communication through natural language understanding. *Exploratory Research in Clinical and Social Pharmacy*. 2024;13:100419.
58. Maleki Varnosfaderani S, Forouzanfar M. The role of AI in hospitals and clinics: Transforming healthcare in the 21st century. *Bioengineering*. 2024;11:337.
59. Sun G, Zhou YH. AI in healthcare: Navigating opportunities and challenges in digital communication. *Frontiers in Digital Health*. 2023;5:1291132.
60. Cinelli M, Quattrociocchi W, Galeazzi A, Valensise CM, Brugnoli E, Schmidt AL, Zola P, Zollo F, Scala A. The COVID-19 social media infodemic. *Scientific Reports*. 2020;10:16598.
61. Richterich A. When open source design is vital: critical making of DIY healthcare equipment during the COVID-19 pandemic. *Health Sociology Review*. 2020;29(2):158–167.
62. Verma N, Grossman D. Self-managed abortion in the United States. *Current Obstetrics and Gynecology Reports*. 2023;12(2):70–75.
63. Moseson H, Bullard KA, Cisternas C, Grosso B, Vera V, Gerdts C. Effectiveness of self-managed medication abortion between 13 and 24 weeks gestation: A retrospective review

of case records from accompaniment groups in Argentina, Chile, and Ecuador. *Contraception*. 2020;102(2):91–98.
64. Berer M. Reconceptualizing safe abortion and abortion services in the age of abortion pills: A discussion paper. *Best Practice and Research Clinical Obstetrics and Gynaecology*. 2020;63:45–55.
65. Chen C, Patterson B, Simpson R, Li Y, Chen Z, Lv Q, Guo D, Li X, Fu W, Guo B. Do fluoroquinolones increase aortic aneurysm or dissection incidence and mortality? A systematic review and meta-analysis. *Frontiers in Cardiovascular Medicine.* 2022;9:949538.
66. Shu Y, Zhang Q, He X, Liu Y, Wu P, Chen L. Fluoroquinolone-associated suspected tendonitis and tendon rupture: A pharmacovigilance analysis from 2016 to 2021 based on the FAERS database. *Frontiers in Pharmacology.* 2022;13:990241.
67. Wexler A. Mapping the landscape of do-it-yourself medicine. *Citizen Science: Theory and Practice*. 2022;7(1):38.
68. Browne J, Jacobson M, Lucki I. Novel targets to treat depression: opioid-based therapeutics. *Harvard Review of Psychiatry*. 2020;28(1):40–59.
69. Ekekezie C, Perler BK, Wexler A, Duff C, Lillis CJ, Kelly CR. Understanding the scope of do-it-yourself fecal microbiota transplant. *The American Journal of Gastroenterology.* 2020;115(4):603–607.
70. Burnside M, Crocket H, Mayo M, Pickering J, Tappe A, de Bock M. Do-it-yourself automated insulin delivery: a leading example of the democratization of medicine. *Journal of Diabetes Science and Technology*. 2020;14(5):878–882.
71. Roberts JTF, Moore V, Quigley M. Prescribing unapproved medical devices? The case of DIY artificial pancreas systems. *Medical Law International*. 2021;21(1):42–68.
72. Heinemann L, Lange K. "Do It Yourself" (DIY)—Automated Insulin Delivery (AID) systems: current status from a German point of view. *Journal of Diabetes Science and Technology*. 2020;14(6):1028–1034.
73. Fincham JE. Negative consequences of the widespread and inappropriate easy access to purchasing prescription medications on the internet. *American Health and Drug Benefits*. 2021;14(1):22–28.
74. Rather IA, Kim BC, Bajpai VK, Park YH. Self-medication and antibiotic resistance: crisis, current challenges, and prevention. *Saudi Journal of Biological Sciences.* 2017;24(4):808–812.
75. Lescure D, Paget J, Schellevis F, van Dijk L. Determinants of self-medication with antibiotics in European and Anglo-Saxon countries: a systematic review of the literature. *Frontiers in Public Health*. 2018;6:370.
76. Torres NF, Chibi B, Middleton LE, Solomon VP, Mashamba-Thompson TP. Evidence of factors influencing self-medication with antibiotics in low and middle-income countries: a systematic scoping review. *Public Health*. 2019;168:92–101.

77. Ayukekbong JA, Ntemgwa M, Atabe AN. The threat of antimicrobial resistance in developing countries: causes and control strategies. *Antimicrobial Resistance and Infection Control*. 2017;6(1):47.
78. Peciña M, Karp JF, Mathew S, Todtenkopf MS, Ehrich EW, Zubieta JK. Endogenous opioid system dysregulation in depression: implications for new therapeutic approaches. *Molecular Psychiatry*. 2019;24(4):576–587.
79. Wexler A. Recurrent themes in the history of the home use of electrical stimulation: transcranial direct current stimulation (tDCS) and the medical battery (1870–1920). *Brain Stimulation*. 2017;10(2):187–195.
80. Edenfield AC, Holmes S, Colton JS. Queering tactical technical communication: DIY HRT. *Technical Communication Quarterly*. 2019;28(3):177–191.
81. Alyafei A, Easton-Carr R. The Health Belief Model of behavior change. In: StatPearls.Internet Treasure Island (FL): StatPearls Publishing; 2025 Jan. Updated 2024 May 19. Available from: https://www.ncbi.nlm.nih.gov/books/NBK606120
82. Taflinger S, Sattler S. A situational test of the health belief model: How perceived susceptibility mediates the effects of the environment on behavioral intentions. *Social Science and Medicine*. 2024;346:116715.
83. Kim S, Kim S. Analysis of the impact of health beliefs and resource factors on preventive behaviors against the COVID-19 pandemic. *International Journal of Environmental Research and Public Health*. 2020;17(22):8666.
84. AlMaskari AM, Al-Mahrouqi T, Al Lawati A, Al Aufi H, Al Riyami Q, Al-Sinawi H. Students' perceptions of AI mental health chatbots: An exploratory qualitative study at Sultan Qaboos University. *BMJ Open*. 2025;15(10):e103893.
85. Aggarwal A, Tam CC, Wu D, Li X, Qiao S. Artificial intelligence-based chatbots for promoting health behavioral changes: Systematic review. *Journal of Medical Internet Research*. 2023;25:e40789.
86. Naji GMA, Yuan F, Azzura N, Danish F, Ateeq A, Ibrahim SB, Hakimi H, Abdollah AB, Iskandar YHP. Factors influencing perceived benefits and behavioral intention to use mental health chatbots among professional employees: An empirical study. *Frontiers in Digital Health*. 2025;7:1606273.
87. Lee AT, Ramasamy RK, Subbarao A. Understanding psychosocial barriers to healthcare technology adoption: A review of the Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology frameworks. *Healthcare*. 2025;13(3):250.
88. Alsyouf A, Lutfi A, Alsubahi N, Alhazmi FN, Al-Mugheed K, Anshasi RJ, Alharbi NI, Albugami M. The use of a technology acceptance model to predict patients' usage of a personal health record system: The role of security, privacy, and usability. *International Journal of Environmental Research and Public Health*. 2023;20(2):1347.
89. Kleine AK, Schaffernak I, Lermer E. Exploring predictors of AI chatbot usage intensity among students: Within- and between-person relationships based on the technology acceptance model. *Computers in Human Behavior: Artificial Humans*. 2025;3:100113.

90. Adel N. The impact of digital literacy and technology adoption on financial inclusion in Africa, Asia, and Latin America. *Heliyon*. 2024;10(24):e40951.
91. Ayo-Ajibola O, Davis RJ, Lin ME, Riddell J, Kravitz RL. Characterizing the adoption and experiences of users of artificial intelligence-generated health information in the United States: cross-sectional questionnaire study. *Journal of Medical Internet Research*. 2024;26:e55138.
92. Ajalo E, Mukunya D, Nantale R, Kayemba F, Pangholi K, Babuya J, Langoya Akuu S, Namiiro AM, Nsubuga YB, Mpagi JL, Musaba MW, Oguttu F, Kuteesa J, Mubuuke AG, Munabi IG, Kiguli S. Widespread use of ChatGPT and other artificial intelligence tools among medical students in Uganda: a cross-sectional study. *PLOS One*. 2025;20(1):e0313776.
93. Britannica. Edo | Benin City, Igarra, Uzebba. https://www.britannica.com/place/Edo-state-Nigeria. 2025 [cited 2025 Mar 19].
94. Edo State Government. Home. https://edostate.gov.ng/. [cited 2025 Mar 19].
95. Niger Delta Budget Monitoring Group. Niger Delta Budget Monitoring Group. https://www.nigerdeltabudget.org/. [cited 2025 Mar 19].
96. Edo State Government. Edo State Medium Term Basic Education Strategic Plan (ESMTBESP) 2024–2027. https://edostate.gov.ng/wp-content/uploads/2025/03/2024-2027-ESMTBESP_Document.pdf. 2021 [cited 2026 Mar 10].
97. Ezemonye M, Emeribe C. Socio-economic determinants of household energy consumption pattern in Benin City, Edo State, Nigeria. International Journal of Renewable Energy and Environment. 2016;2:102–11.
98. Uwadiegwu BO. Evaluation of the impacts of tourism on the physical and socio-economic environment of Oredo Local Government Area, Edo State, Nigeria. Caribbean J Sci Technol. 2014;2:282–94.
99. Obialo M. List of NUC Accredited Universities in Nigeria (2026) – Nigerian Search Guide. https://www.nigeriansearchguide.com/list-of-nuc-accredited-universities-in-nigeria/. 2026 [cited 2026 Mar 10].
100. University of Benin. About Us. https://www.uniben.edu/about-uniben.html. [cited 2026 Mar 10].
101. University of Benin, Office of the Dean of Students. Student count (undergraduate full-time) as at May 25, 2025 [unpublished institutional document]. Benin City: University of Benin; 2025. See appendix 1
102. Latitude.to. GPS coordinates of University of Benin (Nigeria): Latitude 6.3337, Longitude 5.6001. http://latitude.to:8080/articles-by-country/ng/nigeria/26486/university-of-benin-nigeria. [cited 2025 Feb 2].
103. Cochran WG. Sampling techniques. 3rd ed. New York: John Wiley & Sons; 19(7):71–422.
104. Abdelwahed A, Abd El-Nasser M, Heih OQ, Suleiman AM, Khader AM, Ibrahim RA, Abdelnaby MR, Hamad F, Radwan E, Srour AM, HealthTech Alliance, Ghallab MM. Public attitudes and practices toward using AI chatbots for healthcare assistance: a

multinational cross-sectional study. BMC Health Services Research. 2025;25:article number. Available from: https://www.springernature.com/gp/journal/12913

105. International Labour Organization. International standard classification of occupations [Internet]. Geneva: ILO; 2012 [cited 2026 Mar 24]. Available from: https://www.ilo.org/sites/default/files/wcmsp5/groups/public/@dgreports/@dcomm/@publ/documents/publication/wcms_172572.pdf

APPENDIX I

INFORMED CONSENT FORM

TITLE OF STUDY

Use of Artificial Intelligence Chatbots in Facilitating Self-Medication Practices Among Undergraduate Students of the University of Benin (UNIBEN)

INSTITUTION

Department of Public Health and Community Medicine, College of Medical Sciences, University of Benin, Benin City.

PRINCIPAL INVESTIGATOR

Ekanem Grace Nseabasi

SUPERVISOR

Prof. Andrew I. Obi

FINANCIAL SPONSORSHIP

This research work is financially sponsored by the principal investigator.

PURPOSE OF RESEARCH

The purpose of this research work is to assess knowledge, attitudes, prevalence of Use of Artificial Intelligence Chatbots in Facilitating Self-Medication Practices Among Undergraduate Students of the University of Benin

PROCEDURES

Participants (Undergraduate Students of the University of Benin) will be asked questions regarding the knowledge, attitudes, prevalence and factors associated with the use of AI chatbots for self-medication among undergraduate students

CONFIDENTIALITY

All information collected would be kept confidential and stored securely. Data collected would he anonymized and only accessible to the research team.

COMPENSATION

Participants will not receive any compensation for their participation.

VOLUNTARY PARTICIPATION

Your participation in this study is voluntary. You may withdraw from the study at any time without any consequences.

RISKS

There are no risks associated with participation in this study.

BENEFITS

Participants would contribute to important research that may help improve public health promotion strategies. The results obtained from this research work would help us assess the knowledge, attitudes prevalence and factors are associated with the use of AI chatbots for self-medication among undergraduate students.

CONTACT INFORMATION

If you have any questions or concerns regarding this research work, please contact...

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OR

Department of Public Health and Community Medicine, UBTH, Benin City, Edo State, Nigeria.

Ethics and Research Committee,

Email: edohrec@gmail.com, dromoyebello@yahoo.com

IF THERE IS ANY PORTION OF THIS CONSENT AGREEMENT THAT YOU DO NOT UNDERSTAND, ASK THE FIELD WORKER OR INVESTIGATOR BEFORE SIGNING.

Please, sign below if you have agreed to participate in the study.

Title of Research: Use of Artificial Intelligence Chatbots in Facilitating Self-Medication Practices Among Undergraduate Students of the University of Benin (UNIBEN)

Dear Respondent,

I am a final year medical student of the College of Medical Sciences, University of Benin, conducting a research study on the use of artificial intelligence (AI) chatbots in facilitating self-medication practices among undergraduate students of the University of Benin (UNIBEN). This study aims to assess students' awareness, patterns of use, and the extent to which AI chatbots influence decisions related to self-medication.

Your participation in this study is entirely voluntary. You are free to decline participation or withdraw from the study at any time without any consequences. All information provided will be treated with strict confidentiality and will be used solely for academic and research purposes. No personal identifying information will be collected. The questionnaire will take approximately 10–15 minutes to complete.

There are no direct risks associated with participating in this study. While there may be no immediate personal benefit, your responses will contribute to a better understanding of how AI chatbot use may influence self-medication practices among university students. The findings may help guide future health education strategies and policy recommendations within the university community.

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

Signature/Thumbprint of Participant: ____________________

Date: ____________________

For any questions or concerns about this study, please contact:

Principal Investigator: ____________________

Email: ____________________

Phone: ____________________

APPENDIX II

QUESTIONNAIRE ON THE USE OF ARTIFICIAL INTELLIGENCE CHATBOTS IN FACILITATING SELF-MEDICATION PRACTICES AMONG UNDERGRADUATE STUDENTS OF THE UNIVERSITY OF BENIN (UNIBEN)

Instruction: This questionnaire is strictly for academic purposes. All responses will be treated confidentially. Please tick (✓) the option that best applies to you. (Single response unless otherwise stated). Follow the skip instructions where applicable.

Section A: Socio-Demographic Characteristics

1. Age (years): _______
2. Sex: ☐ Male ☐ Female
3. Religion: ☐ Christianity ☐ Islam ☐ African Traditional Religion ☐ Others (specify): ___________
4. Marital Status: ☐ Single ☐ Married ☐ Cohabitating ☐ Divorced ☐ Separated ☐ Others (specify): ___________
5. Ethnic Group: ___________________
6. Faculty: ☐ Basic Medical Sciences ☐ Clinical Sciences ☐ Life Sciences ☐ Physical Sciences ☐ Arts ☐ Social Sciences ☐ Education ☐ Engineering ☐ Management Sciences ☐ Other (specify): ___________
7. Department: ___________________
8. Level of study: ☐ 100 ☐ 200 ☐ 300 ☐ 400 ☐ 500 ☐ 600
9. Place of residence: ☐ On-campus ☐ Off-campus
10. Monthly allowance (Naira): ☐ <10,000 ☐ 10,000–20,000 ☐ 21,000–30,000 ☐ 31,000–50,000 ☐ >50,000
11. Guardian's highest level of education:
☐ No formal education ☐ Primary ☐ Secondary ☐ Tertiary ☐ Postgraduate ☐ Others (specify): _______
12. Guardian's occupation: ___________________
13. Estimated guardian's monthly income (Naira):
☐ <50,000 ☐ 50,000–100,000 ☐ 101,000–200,000 ☐ 201,000–500,000 ☐ >500,000 ☐ Not sure

Section B: Knowledge of Artificial Intelligence (AI) Chatbots

14. Have you heard of Artificial Intelligence (AI) chatbots (e.g., ChatGPT, Gemini, Google Assistant, Siri, Ada, Woebot, Medisafe)?
    ☐ Yes ☐ No
    (If No, skip to Section F)

15. What is your main source of information/knowledge about AI chatbots? (Multiple response)
    ☐ Lectures ☐ Internet ☐ Social media ☐ Friends ☐ Workshops ☐ Online courses ☐ Others (specify): ___________

16. AI chatbots are best described as:
    ☐ Computer programs that simulate human conversation using AI
    ☐ Human operators responding to messages
    ☐ Mobile applications for social media only
    ☐ I am not sure

17. Which of the following AI chatbots are you aware of? (Multiple response)
    ☐ ChatGPT ☐ Gemini ☐ Google Assistant ☐ Siri ☐ Alexa ☐ Ada ☐ Woebot ☐ Medisafe ☐ Social media chatbots ☐ Others (specify): ___________

18. Have you ever received any formal training on AI or AI chatbots? ☐ Yes ☐ No

19. Do you know that AI chatbots can provide information about medicines and health conditions? ☐ Yes ☐ No

Section C: Attitudes Toward the Use of AI Chatbots for Self-Medication

Please indicate your level of agreement with each statement.

S/N	Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
20	AI chatbots are useful for obtaining drug-related information					
21	AI chatbots provide reliable information for self-medication					
22	AI chatbots make it easier to decide which medicines to use without seeing a					

	doctor					
23	AI chatbots help in understanding drug dosage and instructions					
24	Using AI chatbots for self-medication saves time and money					
25	I feel comfortable discussing minor health problems with AI chatbots					
26	Information from AI chatbots influences my decision to self-medicate					
27	AI chatbots can increase the risk of inappropriate drug use					
28	AI chatbots should not replace healthcare professionals					
29	AI chatbots can support but not replace professional medical advice					
30	AI chatbots have benefits in facilitating self-medication					
31	AI chatbots have drawbacks that may negatively affect health					
32	AI chatbots can completely replace clinical consultation					

Section D: Prevalence and Pattern of AI Chatbot Use

33. Do you own a mobile device? ☐ Yes ☐ No
    (If No, skip to Section F)

34. How often do you use your mobile device? ☐ Very often ☐ Often ☐ Occasionally ☐ Rarely ☐ Never

35. Under what circumstances do you usually use your mobile device?
☐ Social media ☐ Academic purposes ☐ Gaming ☐ Health information ☐ Others (specify): ___________

36. On average, how many hours do you spend on social media daily?
☐ 30 minutes ☐ 1 hour ☐ 2–3 hours ☐ 4–5 hours ☐ More than 5 hours ☐ Others (specify): _______

37. Have you ever used an AI chatbot for any purpose? ☐ Yes ☐ No
(If No, skip to Section E)

38. For what purposes have you used AI chatbots? (Multiple response)
☐ Academic work ☐ Social interaction ☐ Entertainment ☐ Health information ☐ Others (specify): ___________

39. Have you ever used an AI chatbot for health-related information? ☐ Yes ☐ No
(If No, skip to Question 47)

40. Have you ever used an AI chatbot to assist in self-medication? ☐ Yes ☐ No
(If No, skip to Question 47)

41. How often do you use AI chatbots for self-medication?
☐ Very often ☐ Often ☐ Occasionally ☐ Rarely ☐ Never

42. Which AI chatbot(s) have you used for self-medication? (Multiple response)
☐ ChatGPT ☐ Gemini ☐ Google Assistant ☐ Siri ☐ Ada ☐ Woebot ☐ Medisafe ☐ Social media chatbots ☐ Others (specify): ___________

43. Did consulting an AI chatbot result in you taking medication without seeing a healthcare professional? ☐ Yes ☐ No

44. Did information from the AI chatbot influence your decision to self-medicate? ☐ Yes ☐ No

45. What condition or illness did you use it for?
☐ Malaria ☐ Typhoid ☐ Headache ☐ Cough/Cold ☐ Stomach upset ☐ Skin condition ☐ Menstrual pain ☐ Others (specify): ___________

46. Did it produce the expected health outcome? ☐ Yes ☐ No ☐ Not sure

47. Have you experienced any negative outcome from using AI chatbot information? ☐ Yes ☐ No
    If yes, specify (optional): ____________________
48. Would you recommend the use of AI chatbots for self-medication to others?
    ☐ Definitely Yes ☐ Probably Yes ☐ Not Sure ☐ Probably No ☐ Definitely No
49. Under what circumstances would you recommend AI chatbots to others?
    ____
50. Would you continue using AI chatbots for self-medication in the future?
    ☐ Yes ☐ No ☐ Not sure
51. How often do you use your smart device specifically for health-related purposes?
    ☐ Very often ☐ Often ☐ Occasionally ☐ Rarely ☐ Never
52. Are you aware of any University of Benin policy restricting or guiding the use of AI tools for academic or health purposes?
    ☐ Yes ☐ No ☐ Not sure
53. Do you think there should be institutional guidelines regulating students' use of AI chatbots for health information?
    ☐ Yes ☐ No ☐ Not sure
54. Have institutional policies or academic rules influenced your decision to use or not use AI chatbots?
    ☐ Yes ☐ No ☐ Not sure

Section E: Perceived Risks and Influencing Factors

Please indicate your response to the following statements:

S/N	**Statement**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
55	AI chatbot-assisted self-medication can lead to drug misuse					
56	There should be guidelines regulating AI chatbots used for health information					
57	Peer pressure can influence a student's decision to use AI chatbots for self-					

	medication					
58	Having regular internet access influences the use of AI chatbots for health purposes					
59	Interacting with friends or colleagues who use AI chatbots increases the likelihood of personal use					

60. Students should be educated on the safe use of AI chatbots for health purposes.
☐ Yes ☐ No

61. What are the possible negative implications of using AI chatbots for self-medication? (Multiple response)
☐ Wrong diagnosis ☐ Incorrect dosage ☐ Adverse drug reaction ☐ Drug interactions ☐ Delay in seeking professional care ☐ Drug resistance ☐ Others (specify): ____________

APPENDIX III

ETHICAL APPROVAL FROM EDO STATE MINISTRY OF HEALTH, HEALTH RESEARCH ETHICS COMMITTEE

HEALTH RESEARCH
ETHICS COMMITTEE (HREC)

UNIVERSITY OF BENIN TEACHING HOSPITAL
P.M.B. 1111 BENIN CITY NIGERIA Telephone 052-600418 Website: ubth.org

CHIEF MEDICAL DIRECTOR	DIRECTOR OF ADMINISTRATION	CHAIRMAN
Prof. (Mrs) I.N Ize-Iyamu	Jim Uwadie, Esq	Prof. (Mrs.) Antoinette N. Ofili

HREC OFFICE:
Committee email: ubthresearchethics@gmail.com
Registration Number:
NHREC-UBTH-HREC/24/12/2022B

PROTOCOL NUMBER: ADM/E 22/A/VOL. VII/14865491272106

PROPOSAL TITLE: "USE OF ARTIFICIAL INTELLIGENCE CHATBOT IN FACILITATING SELF-MEDICATION PRACTICES AMONG UNDERGRADUATE STUDENTS IN BENIN CITY"

PRINCIPAL INVESTIGATOR(S): EKANEM GRACE NSEABASI

DEPARTMENT/INSTITUTION: DEPARTMENT OF PUBLIC HEALTH AND COMMUNITY MEDICINE, SCHOOL OF MEDICINE, UNIVERSITY OF BENIN, BENIN CITY, EDO STATE, NIGERIA

DATE CONSIDERED: MARCH 18TH, 2026

DECISION OF THE COMMITTEE: APPROVED

THIS APPROVAL DATES 18/03/2026 TO 17/03/2027. IF THERE IS DELAY IN STARTING THE RESEARCH, PLEASE INFORM THE HREC SO THAT THE DATES OF APPROVAL CAN BE ADJUSTED ACCORDINGLY

REMARK:

CHAIRMAN: PROF. (MRS) A.N. OFILI SIGNATURE & DATE: 18/3/2026

SUPERVISOR (S): PROF A.I. OBI

DECLARATION BY INVESTIGATOR(S):
PROTOCOL NUMBER (please quote in all enquiries)

Note that no participant accrual or activity related to this research may be conducted outside of these dates and you **are to furnish the committee with the research activities at the completion of the study.** All informed consent forms used in this study must carry the HREC assigned number and duration of HREC approval of the study. In multiyear research, endeavor to submit your annual report to the HREC early in order to obtain renewal of your approval and avoid disruption of your research. No changes are permitted in the research without prior approval by the HREC except in circumstances outlined in the Code. The HREC reserves the right to conduct compliance visit your research site without previous notification.

Signature & Date.................................

ubthresearchethics@gmail.com Registration Number: NHREC/24/01/2020

APPENDIX IV

INTELLECTUAL PROPERTY & TECHNOLOGY TRANSFER OFFICE (IPTTO)

Vice Chancellor's Office
University of Benin
PMB1154, Benin City, Nigeria

CLEARANCE FORM

DATE: 13/5/26

NAME: EKANEM GRACE NSEABASI

MATRIC NO: MED1807393

DEPARTMENT: MEDICINE

FACULTY: MEDICINE

SESSION OF GRADUATION: 2024/25

DIRECTOR
IPTTO
UNIBEN, BENIN CITY

Head Of Unit (IPTTO):