UPTAKE AND LEVEL OF UTILISATION OF ARTIFICIAL INTELLIGENCE IN CLINICAL ASSESSMENT AMONG HEALTHCARE PROFESSIONALS IN THE UNIVERSITY OF BENIN TEACHING HOSPITAL

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DECLARATION

I hereby declare that this research project titled "**UPTAKE AND LEVEL OF UTILISATION OF ARTIFICIAL INTELLIGENCE IN CLINICAL ASSESSMENT AMONG HEALTHCARE PROFESSIONALS IN THE UNIVERSITY OF BENIN TEACHING HOSPITAL**" was carried out by **IDEMUDIA ELOGHOSAVBUMWEN ANGEL** with matriculation number **MED1807409** under supervision of Professor A. I. Obi and has not been submitted in part or in full for any purpose.

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CERTIFICATION

This is to certify that this research study titled "**uptake and level of utilisation of artificial intelligence in clinical assessment among healthcare professionals in the university of benin teaching hospital**" was conducted by **Idemudia Eloghosavbumwen Angel** with matriculation number MED1807409 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

I dedicate this project to God Almighty for His grace, strength, wisdom, and guidance throughout the course of this study.

I also dedicate this work to the loving memory of my late father, Associate Prof. J. O. Idemudia, whose love, guidance, and inspiration continue to live in my heart and motivate me every day.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AI-CDS	Artificial Intelligence–based Clinical Decision Support
CDS	Clinical Decision Support
DL	Deep Learning
ENT	Ear, Nose and Throat
EHR	Electronic Health Record
ICT	Information and Communication Technology
LLM	Large Language Model
LMICs	Low- and Middle-Income Countries
ML	Machine Learning
NHTF	National Health Technology Fund
NLP	Natural Language Processing
SPSS	Statistical Package for the Social Sciences
UBTH	University of Benin Teaching Hospital
UTAUT	Unified Theory of Acceptance and Use of Technology
WHO	World Health Organization

DEFINITION OF TERMS

Artificial Intelligence (AI):

The ability of computer systems or machines to perform tasks that normally require human intelligence, such as learning, reasoning, decision-making, pattern recognition, and language processing.

Clinical Decision Support Systems (CDSS):

Computer-based systems that analyze clinical data to assist healthcare professionals in making informed diagnostic and treatment decisions.

Clinical Support:

The use of tools, systems, or technologies to assist healthcare professionals in diagnosis, treatment planning, patient monitoring, documentation, and workflow management without replacing clinical judgement.

Deep Learning (DL):

A subset of machine learning that uses multi-layered neural networks to analyze complex data patterns, commonly applied in medical imaging and predictive analytics.

Digital Health Infrastructure:

The availability of hardware, software, internet connectivity, power supply, and IT support required to implement and sustain AI-based clinical tools.

Healthcare Professionals:

Individuals involved in the delivery of patient care and clinical decision-making, including medical doctors, nurses, pharmacists, medical laboratory scientists, and physiotherapists.

Large Language Models (LLMs):

Advanced AI models trained on large datasets to understand, generate, and analyze human language for tasks such as text summarization, documentation, and clinical information support.

Machine Learning (ML):

A subset of artificial intelligence that enables computer systems to learn from data and improve performance without being explicitly programmed.

ABSTRACT

Background: Artificial Intelligence (AI) is transforming global healthcare by enhancing diagnostics and clinical workflows. However, in resource-constrained settings like Nigeria, the integration of AI remains uneven, often hindered by infrastructure deficits and limited training. While awareness of AI is growing, there is a significant gap between knowledge and actual clinical implementation among healthcare professionals.

Aim: The study aimed to assess the uptake and level of utilisation of artificial intelligence in clinical support among healthcare professionals at the University of Benin Teaching Hospital (UBTH). Specifically, it determined the level of knowledge, attitudes, and factors influencing AI adoption within the institution.

Methods: An analytical cross-sectional study design was employed, involving 409 healthcare professionals including doctors, nurses, pharmacists, medical laboratory scientists, and physiotherapists. Participants were selected using a multistage sampling technique. Data were collected through structured, pre-tested, self-administered questionnaires comprising sections on socio-demographic characteristics, level of knowledge, attitude, uptake and level of utilisation, and factors influencing AI use. Knowledge, uptake and level of utilisation scores were categorized based on a 70% cut-off, while attitud was assessed using a 5-point likely scale which was grouped into appropriate and inappropriate responses and scored using a cut-off of 70%. Data were analyzed using IBM SPSS version 27.0. Descriptive and inferential statistics were used to identify predictors of AI uptake and utilisation. Statistical significance was set at $p < 0.050$, and 95% confidence interval.

Results: Among the 409 healthcare professionals surveyed, the majority were aged 20–29 years (50.4%), female (63.3%), Christians (97.3%), and single (61.9%). Nurses constituted the largest professional group (47.4%), followed by doctors (39.9%), while most respondents were junior staff (55.7%) with less than 10 years of work experience (85.3%).

All respondents (100%) were aware of AI, with 61.1% demonstrating good knowledge. While more than half (51.3%) had ever used an AI tool, predominantly ChatGPT, routine clinical utilisation remained low. Slightly more than half (51.1%) of the respondents expressed a negative attitude toward AI in clinical assessment. Positive attitudes (OR = 1.59; 95% CI: 1.034–2.447; $p = 0.035$) and higher educational qualifications (OR = 3.169; 95% CI: 1.040–9.651; $p = 0.042$) were significant predictors of AI uptake and utilisation. Major barriers identified included unclear ethical guidelines, patient's attitude towards AI use, infrastructural limitations (such as unstable power and internet), and concerns regarding patient data privacy. However, patients' attitude was the only significant predictor ($p = 0.049$)

Conclusion: While healthcare professionals at UBTH have relatively high awareness and initial uptake of AI, sustained and routine utilisation remains constrained by negative attitudes and perceived patient's attitude. These perceptions appear to shape hesitancy in fully integrating AI into clinical workflows. To address this, there is an urgent need for structured institutional training, clear ethical frameworks, and improved digital infrastructure to shift attitudes and support safe, routine and effective integration of AI into clinical practice.

Keywords: Artificial Intelligence, Clinical Assessment, Healthcare Professionals, Uptake, Utilisation, UBTH, Nigeria.

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND

Artificial Intelligence (AI) is the ability of a computer or machine to perform tasks that typically require human intelligence, including speech recognition, visual perception, decision-making, and language translation.[1] AI has the potential to transform what was once thought impossible into reality. With the advancement of AI technology, new possibilities and opportunities will continue to emerge. The field of AI traces its origins to 1956, when John McCarthy first introduced the term at a workshop held at Dartmouth College.[2]

AI encompasses various techniques, including machine learning (ML), deep learning (DL), and natural language processing (NLP). Large Language Models (LLMs) are a type of AI algorithm that leverage deep learning and vast data sets to understand, generate, summarize, and predict text-based content. Designed for diverse NLP applications, LLMs can perform tasks such as text generation, translation, summarization, rewriting, classification, and sentiment analysis. NLP, a branch of AI, enables interaction between computers and humans by processing and generating natural language through techniques like text mining, speech recognition, sentiment analysis, and machine translation. Over time, AI has evolved significantly, shifting from rule-based systems to advanced ML and DL models.[3] Examples of NLP and AI applications include LLMs like GPT-3, ChatGPT, Microsoft Copilot, Google Bard (Gemini). NLP-powered tools include voice-operated GPS, customer service chatbots, language translation, search query auto-completion.[4]

AI has rapidly advanced in recent years, finding applications in finance, law, cybersecurity, manufacturing, and medicine. In healthcare, it is transforming clinical decision-making, diagnostics, and patient care. Technologies like machine learning, natural language processing, and computer vision are increasingly aiding medical professionals in handling complex tasks.[1]

Artificial intelligence in medicine involves using machine learning models to analyse medical data, providing healthcare professionals with valuable insights that enhance patient care and health outcomes. Applications of AI in medicine include the use of AI in disease detection and diagnosis, personalized treatment plans, medical imaging, clinical trial efficiency and accelerated drug development. [5] AI-powered systems analyse vast amounts of patient data to assist in diagnosing diseases and recommending treatments, often matching or surpassing human accuracy. In drug discovery, AI accelerates research by predicting molecular interactions and potential drug efficacy, significantly reducing development timelines. Additionally, AI-driven chatbots and virtual assistants improve physician-patient communication, offering instant information and support to enhance engagement and satisfaction. AI also streamlines medical documentation by automating the transcription of prescriptions and clinical notes, reducing administrative burdens on healthcare professionals. Furthermore, AI plays a crucial role in remote treatment through telemedicine, enabling efficient monitoring and care delivery, particularly in underserved regions. These advancements highlight AI's potential to transform healthcare by improving accessibility, accuracy, and overall patient outcomes.[6]

Artificial intelligence (AI) has become an integral part of clinical workflows in developed countries, significantly improving healthcare delivery across various domains. In diagnostics and treatment planning, AI-driven systems analyse vast amounts of patient data to assist in identifying diseases and recommending personalized treatment strategies, often achieving accuracy comparable to or exceeding that of human professionals. The pharmaceutical industry is also leveraging AI to accelerate drug discovery and development, with major companies implementing AI training programs to enhance workforce proficiency in regulatory compliance and research. Additionally, AI-powered tools, such as automated medical scribes, are streamlining clinical documentation by transcribing and analysing spoken notes, reducing administrative burdens for healthcare professionals and allowing them to focus more on patient care. In personalized medicine, AI plays a crucial role in predicting patient responses to treatment, as seen in research collaborations using digital twins of tumours to develop targeted therapies. Moreover, federated learning approaches enable AI models to be trained across decentralized data sources while preserving patient privacy, fostering collaborative medical research and innovation. These advancements illustrate AI's transformative impact on clinical workflows, leading to more efficient healthcare systems and improved patient outcomes in developed nations.(3) AI-driven robotic systems are used for various procedures, from minimally invasive surgeries to complex open-heart operations. This advanced technology provides a magnified, 3D view of the surgical site and has resulted in fewer complications, reduced pain, and faster recovery times for patients.(7)

Notable AI applications used in healthcare by medical professionals include; H2O.ai, PathAI, Viz.ai, FWA360Leads, NDIVIA. H2O.ai analyses health data to identify patterns and predict patient outcomes, enabling doctors to tailor treatment plans based on genetics, medical history, and lifestyle. PathAI, a global leader in AI-powered pathology, enhances diagnostics and patient outcomes, excelling in drug development for complex diseases. Its subsidiary, PathExplore, provides high-resolution tumour microenvironment (TME) analysis from H&E whole-slide images, currently available for breast, colorectal, gastric, non-small cell lung, pancreatic, prostate, renal cell carcinoma, and melanoma. Viz.ai is suited for stroke diagnosis, treatment, and prevention. NDIVIA provides solutions for medical imaging, natural language processing, and drug discovery, enabling healthcare providers to leverage AI more effectively for faster diagnoses and improved treatment plans.(8)

Despite its growing prominence, the adoption and utilization of AI among medical doctors remain uneven, particularly in resource-constrained settings like Nigeria. AI knowledge in developing countries is still at a foundational level, with many medical professionals perceiving the technology as unfamiliar. [1] Research has shown that while AI is gaining traction globally, many healthcare workers, especially in developing countries like Nigeria, have limited knowledge of its applications and benefits. [9]. Attitudes toward AI play a pivotal role in its acceptance and integration into healthcare systems. While some medical professionals view AI as a valuable tool for improving diagnostic accuracy and reducing medical errors, others express concerns about its potential to replace human expertise or introduce ethical and legal challenges. Research has shown that in Nigeria, healthcare workers acknowledged the benefits of AI but were apprehensive about job displacement and the ethical implications of its use [9].

The level of AI usage among medical doctors varies widely across different healthcare settings. In developed countries, AI is increasingly being used in specialties such as radiology, pathology, and oncology for tasks like image analysis, risk prediction, and treatment planning. However, in resource-limited settings like Nigeria, the adoption of AI remains limited due to certain factors.[9] These factors influence the adoption and utilization of AI in healthcare, including knowledge, attitudes, infrastructure, training, and ethical considerations. In Nigeria, challenges such as limited internet access, inadequate funding, and a lack of AI-specific training programs hinder the widespread adoption of AI in healthcare. Additionally, concerns about data privacy, liability, and the potential for AI to replace human jobs contribute to hesitancy among healthcare professionals.[1]

The Nigerian government's collaboration with Google, marked by a ₦2.8 billion grant to Data Science Nigeria, aims to enhance AI talent development nationwide.[10] This initiative aligns with the government's broader strategy to integrate AI across various sectors, including healthcare. By investing in AI education and upskilling programs, the government is building a foundation for innovative healthcare solutions. For instance, AI-driven projects like ADVISER have been deployed to optimize child vaccination efforts, demonstrating AI's potential to improve healthcare delivery.[11] Additionally, the establishment of the National Health Technology Fund (NHTF) supports the research and development of healthcare technologies, further promoting the adoption of smart healthcare solutions.[12] These efforts collectively aim to enhance healthcare outcomes, increase efficiency, and ensure equitable access to medical services across Nigeria.

Healthcare professionals refer to individuals or organisations that deliver medical care to people. This group covers a diverse range of professionals, including doctors, nurses, pharmacists, and specialists, as well as institutions such as hospitals, clinics, and broader healthcare systems. The term spans an extensive array of services, from preventive care and emergency response to diagnosis, surgical procedures, rehabilitation, and the long-term management of chronic illnesses.

The University of Benin Teaching Hospital (UBTH) is a leading tertiary healthcare institution in Nigeria, playing a critical role in advancing medical practice and research. However, the extent to which healthcare providers in UBTH are leveraging AI to complement clinical support remains underexplored[9]. At the University of Benin Teaching Hospital (UBTH), incorporating AI-driven technologies could enhance disease diagnosis, streamline patient management, and optimize treatment plans.[5] By leveraging AI for medical imaging, predictive analytics, and administrative efficiency, UBTH has the opportunity to improve healthcare delivery and advance research in Nigeria’s medical landscape. However, its successful adoption depends on the level of knowledge, attitudes, and usage patterns among the healthcare providers, as well as the factors that influence its implementation.

1.2 STATEMENT OF THE PROBLEM

Globally, Artificial Intelligence (AI) has rapidly transformed healthcare delivery worldwide. AI-related research now spans over 98% of scientific disciplines, reflecting its widespread diffusion across medicine and allied health sciences. In clinical settings, physician engagement with AI has increased substantially, with approximately 66% of physicians reporting the use of AI tools, primarily for clinical documentation, summarization, and workflow optimization rather than autonomous diagnostic decision-making.[3]

High-income countries are progressively embedding AI into diagnostics, treatment planning, predictive analytics, and health system management. Evidence suggests that AI-supported systems improve operational efficiency, enhance diagnostic accuracy, reduce medical errors, and lower long-term healthcare costs through optimized resource utilization.[19] As a result, AI integration is increasingly becoming a benchmark for modern, high-performing healthcare systems.

However, this rapid advancement has created a widening digital divide between technologically advanced health systems and those in low- and middle-income countries (LMICs), contributing to growing global disparities in healthcare quality and access.[14]

In Nigeria, although 85.5% of physicians were aware of AI applications in medicine, only 25.5% had integrated AI into clinical practice [13]. This demonstrates a persistent disconnect between awareness and actual utilization among healthcare professionals.

The University of Benin Teaching Hospital (UBTH), a major tertiary healthcare institution in Nigeria, plays a critical role in healthcare delivery, training, and research. However, like many institutions in low- and middle-income countries, it faces challenges in fully integrating AI into clinical workflows. Globally, while developed countries are increasingly embedding AI into diagnostics, treatment planning, and health system management resulting in improved efficiency and patient outcomes, many developing countries, including Nigeria, continue to lag behind. This disparity contributes to widening global inequalities in healthcare quality and access [14].

Several interrelated factors contribute to the limited adoption of AI in Nigerian healthcare settings. These include infrastructural deficits such as unreliable electricity, poor internet connectivity, and limited access to digital tools, particularly in rural facilities. In addition, weak regulatory frameworks for data privacy and security raise concerns about patient confidentiality, thereby limiting trust in AI systems. A shortage of trained personnel further constrains implementation, as many healthcare workers lack adequate exposure to AI applications. Financial constraints also remain a major barrier, given the high cost of acquiring, deploying, and maintaining AI systems within already constrained healthcare budgets. Ethical and cultural concerns, including mistrust of technology and apprehension about AI-assisted decision-making, further slow adoption.

The limited integration of AI in clinical practice has important implications for healthcare delivery. It contributes to operational inefficiencies, including suboptimal resource allocation, delayed patient scheduling, and increased administrative burden. It also negatively affects patient outcomes by limiting access to AI-supported diagnostic and treatment tools that could enhance clinical accuracy and decision-making [15]. Furthermore, disparities in AI adoption between urban and rural healthcare facilities exacerbate existing inequalities in healthcare access [16]. The absence of AI also delays timely clinical decision-making, as clinicians are unable to rapidly process and interpret large volumes of patient data [17]. Additionally, it restricts institutional research capacity and innovation potential, particularly in tertiary centers such as

UBTH, where AI could support large-scale data analysis, disease surveillance, and improved healthcare planning [18].

Although AI implementation involves significant upfront costs for infrastructure, training, and maintenance, evidence suggests that AI-driven systems can reduce long-term healthcare costs by improving efficiency and reducing medical errors [19]. Nevertheless, financial constraints remain a major limitation in resource-constrained settings such as Nigeria.

Recognizing the potential of AI, efforts are being made to strengthen its adoption in Nigeria. For instance, major investments such as Google's $2.8 billion commitment to AI development in Nigeria aim to strengthen digital and technical capacity, including in healthcare [10]. In addition, national frameworks such as the National Digital Health Strategy seek to promote integration of digital health technologies, including AI, into healthcare delivery systems [20].

Other proposed interventions include public–private partnerships to enhance funding and infrastructure development, investment in capacity building through training in health informatics and AI, and the development of locally tailored AI solutions suited to the Nigerian healthcare context[21].

Despite these initiatives, significant challenges persist. Infrastructure deficits, data security concerns, high implementation costs, resistance from healthcare workers, and the absence of comprehensive regulatory frameworks continue to limit effective adoption. Additionally, most AI tools currently in use are developed in high-income countries and may not fully align with local clinical needs and workflows [23,24]. While concerns about job displacement exist, evidence suggests that AI is more likely to augment rather than replace clinicians by supporting decision-making and automating routine tasks [22].

Although AI holds considerable promise for improving healthcare delivery, its adoption in institutions such as UBTH remains limited due to multiple systemic, institutional, and human factors. Addressing these barriers requires a coordinated, multifaceted approach involving infrastructure development, policy strengthening, workforce training, and sustainable investment to fully realize the benefits of AI in healthcare.

1.3 JUSTIFICATION OF STUDY

Artificial Intelligence (AI) is revolutionizing healthcare globally, offering advancements in diagnostics, treatment planning, and patient management. However, its integration into clinical practice varies across regions, influenced by factors such as knowledge, perception, and infrastructural readiness.[3] This study aims to assess the use of AI among healthcare providers at the University of Benin Teaching Hospital (UBTH), focusing on their knowledge, attitudes, usage, and the factors influencing AI adoption.

By evaluating the current state of AI integration at UBTH, this research will identify existing gaps in knowledge and application among healthcare professionals. Understanding these gaps is crucial for developing targeted interventions, such as tailored training programs, to enhance AI literacy and competence. Such initiatives can lead to improved clinical decision-making, increased efficiency in patient care, and better health outcomes.[25] Furthermore, the findings can inform hospital administrators and policymakers about the necessary infrastructural and policy support required to facilitate AI adoption.

Integrating AI into clinical workflows has the potential to transform public health practice by enabling more accurate diagnoses, personalized treatment plans, and efficient resource allocation.[26] This study's insights can guide the development of strategies to incorporate AI into routine medical practice, thereby enhancing the quality of healthcare services. Additionally, understanding the factors that influence AI adoption can help address potential barriers, ensuring that technological advancements are equitably distributed and accessible, ultimately reducing healthcare disparities.[27]

While previous research has explored AI adoption among healthcare professionals in Nigeria, this study distinguishes itself by focusing specifically on healthcare professionals at UBTH. For instance, a study assessing healthcare professionals in Nigeria revealed that while a majority had good knowledge of AI, there were varying perceptions regarding its integration into healthcare practices.[28] By concentrating on a single institution, this study aims to provide a more detailed and context-specific understanding of AI adoption, considering the unique organizational culture, resources, and patient demographics of UBTH.

This research is expected to add valuable insights into the specific challenges and opportunities associated with AI adoption in a tertiary healthcare institution in Nigeria. By identifying the levels of knowledge, attitudes, and uptake patterns among healthcare professionals, the study can inform the design of targeted educational and policy interventions. Additionally, understanding the factors that influence AI adoption, such as infrastructural readiness, perceived benefits, and potential barriers, can guide future strategies to promote effective integration of AI into clinical practice. Some studies have also been limited by small sample sizes or have not accounted for contextual factors unique to specific institutions.[29] By addressing these limitations, this study aims to provide a more nuanced understanding of AI adoption among healthcare professionals at UBTH.

This study seeks to bridge the knowledge gap regarding AI use among healthcare professionals at UBTH, offering insights that can drive effective integration of AI into clinical practice, enhance public health outcomes, and contribute to the global discourse on AI adoption in healthcare.

1.4 RESEARCH QUESTIONS

1. What is the level of knowledge of Artificial Intelligence applications among healthcare professionals in the University of Benin Teaching Hospital?
2. What are the attitudes of healthcare professionals in the University of Benin Teaching Hospital toward the use of Artificial Intelligence applications in clinical support?
3. What is the uptake of Artificial Intelligence applications among healthcare professionals in the University of Benin Teaching Hospital?
4. What is the level of utilisation of Artificial Intelligence applications among healthcare professionals in the University of Benin Teaching Hospital?
5. What are the factors that influence the uptake and level of utilisation of Artificial Intelligence applications in clinical support among healthcare professionals in the University of Benin Teaching Hospital?

1.5 OBJECTIVES

1.5.1 General Objective

To assess the uptake and level of utilisation of artificial intelligence in clinical support among healthcare professionals in the University of Benin Teaching Hospital, in order to identify gaps and inform strategies for improved integration of AI in clinical practice.

1.5.2 Specific Objectives

1. To assess the level of knowledge of Artificial Intelligence applications in clinical assessment among healthcare professionals in the University of Benin Teaching Hospital
2. To determine the attitude towards the use of Artificial Intelligence applications among healthcare professionals in clinical assessment in the University of Benin Teaching Hospital
3. To determine the uptake and level of utilisation of Artificial Intelligence applications in clinical assessment among healthcare professionals in the University of Benin Teaching Hospital
4. To identify the factors that influence the uptake and level of utilisation of Artificial Intelligence applications among healthcare professionals in the University of Benin Teaching Hospital

CHAPTER TWO

LITERATURE REVIEW

2.1 BACKGROUND TO THE LITERATURE REVIEW

Artificial intelligence (AI) applications are being framed as increasingly viable enablers of clinical support in terms of decision support, triage support, risk prediction, clinical documentation assistance, workflow improvement, or population analysis. In the healthcare setting, applications of AI can be infused in electronic health record systems or run as standalone software applications in order to assist healthcare practitioners in decision-making while lessening the need and time taken in decision-making.(3) Although, the positive impact of AI applications in clinical support can never be guaranteed but are dependent on their comprehension among healthcare practitioners in terms of being well-trusted, accessible, and acceptable in their respective context of healthcare delivery.(40) This gives increased importance to “uptake” (users) and “level of utilisation” (use in clinical work) as outcome measures in health system research in low- as well as middle-income countries because of infrastructural variability in their digital environment of healthcare delivery.(40,48)

There is evidence that the knowledge and perception of clinicians influence the willingness to use the AI system in clinical practice. For instance, it has been found in many surveys carried out among healthcare professionals that there are mixed levels of knowledge and confidence in the use of AI, with the same professionals showing an appreciation of the capabilities of AI in healthcare alongside concerns about the accuracy of the technology, accountability, privacy, and the possibility of errors.(31,32) Also, in Nigeria, in recent surveys, increased knowledge of AI and machine learning in the healthcare industry has been found, but with challenges of knowledge and comprehension of the infrastructures for healthcare delivery, training programs, and the issue of healthcare governance and ethics involving the use of machine learning technology in healthcare, among others.[28,46] These are important aspects in the particular context of tertiary hospitals like the University of Benin Teaching Hospital (UBTH), given the high workload in the healthcare system and the potential utility of supportive technology like the AI system in increasing the efficacy of work, although the utility of digital infrastructure and processes would remain limited in such an environment.

At the clinical level, while there is a natural inclination for adoption in "high-visibility" areas including radiology, pathology, and risk prediction, there is also an increasing use in documentation, summarization of patient histories, following clinical guidelines, and patient communication by newer forms of AI software, including generative AI and "large language models" (LLMs).[38,46] There is also an increased need for clarity on policies, given that clinical software systems, in effect, can affect decision-making indirectly, for instance, through recommendations and summaries. The 2021 WHO guidance on AI in health systems reinforces that ethics, including issues like "transparency, accountability, privacy, and equity," should not follow adoption but should instead "be an integral part" of the adoption process for AI in health systems. [48]

Empirical work also shows that the barriers to adoption lie often in socio-technical rather than purely technical issues. A 2024 scoping review synthesised barriers and facilitators of AI adoption in healthcare and identified some recurring themes: trust and transparency, usability and workflow integration, data quality, organisational readiness, regulatory clarity, and workforce skills.[49] Within tertiary hospitals, even when tools exist, utilisation may remain low if they do not align with clinical workflow, if internet/power is unreliable, if there is inadequate change management, or if clinicians fear medico-legal consequences of AI-assisted decisions.[37,49]

For this study, the focus on knowledge, attitude, uptake, and level of utilisation aligns with a practical evidence gap: many AI discussions in LMICs are aspirational, but adoption in day-to-day clinical support remains under-measured. Nigerian studies already indicate that knowledge and perception are variable, and that institutional factors matter.(28,46) The UBTH-focused design is timely because it can quantify the proportion of healthcare professionals who have ever used AI in clinical support, how often and for what functions they use it, and what factors predict adoption and sustained use. International survey evidence in clinicians supports the examination of intention-to-use and enabling conditions, given these predict actual adoption patterns. (36,37)

Finally, AI adoption needs to be framed within broader system priorities: workforce development, digital health policies, and equity. Ethical and governance frameworks emphasize that AI may widen disparities if benefits accrue only where connectivity, training, and tool access are concentrated.(48,50) Thus, researching UBTH is not simply a matter of quantifying adoption levels but also constitutes a knowledge base from which the leadership of the hospital and policy makers can formulate targeted interventions-such as training programs, governance structures, and workflow integration-to translate pilot enthusiasm to safe, routine clinical utilisation.(36,49)

2.2 THEORETICAL FRAMEWORK

This study is anchored on complementary adoption theories that explain technology use in clinical settings: the Unified Theory of Acceptance and Use of Technology (UTAUT), Technology Acceptance Model (TAM)-based acceptance approaches, and a socio-technical adoption perspective (often expressed in health AI adoption literature as organisational readiness + governance + workflow fit).(49-53) These theories are appropriate because the outcomes (uptake and utilisation) are not purely attitudinal, they represent real behaviour within institutional constraints.

UTAUT: explaining intention and actual use in clinical environments

Recent healthcare AI studies applying UTAUT show that performance expectancy (belief AI improves job performance), effort expectancy (ease of use), social influence (peer/senior expectations), and facilitating conditions (resources and support) predict intention and adoption among clinicians. In a 2025 study using a UTAUT-based approach among physicians and nurses, these constructs were used to explain intention to use medical AI, including the effects of perceived risk.[52] This is directly related to UBTH because "facilitating conditions" encompasses the infrastructure and organizational support aspects that have been cited as requirements for LMIC hospital settings, and "social influence" corresponds to the interplay of professional environment and superiors' influences that affect the adoption process at the department level. [52]

In this study, the concepts within the UTAUT framework align closely with the study objectives. Knowledge may strengthen performance expectancy by improving healthcare professionals' understanding of the potential benefits of artificial intelligence in clinical support. Attitude reflects the combined influence of performance expectancy, perceived risks, and trust in AI systems. Uptake represents the initial behavioural intention and trial use of AI tools, while the level of utilisation reflects sustained and continued use, which is likely influenced by facilitating conditions as well as trust in the technology.[51,52]

TAM-oriented acceptance: usefulness and ease-of-use as practical levers

TAM-based acceptance models remain widely used in clinical decision support adoption research, especially for tools that require workflow integration and repeated use. A 2022 methods paper focused on enabling adoption of machine learning for clinical decision-making highlighted that adoption can be improved by addressing usability, clinician-centred design, integration into workflow, and clear communication of performance and limitations—elements that closely mirror "perceived usefulness" and "perceived ease of use."[54] The practical value of TAM-oriented thinking for UBTH is that it turns adoption into modifiable targets: training improves perceived ease-of-use; clinical relevance improves perceived usefulness; and transparency improves trust.

Within the UBTH setting, constructs derived from the TAM support the design of the study instrument for assessing factors influencing AI utilisation. These constructs guide the measurement of perceived usefulness, including whether healthcare professionals believe AI can save time, improve clinical decision-making, and reduce errors in practice. They also inform the assessment of perceived ease-of-use, such as the extent to which AI systems are considered easy to learn and whether their interfaces are clear and user-friendly. In addition, behavioural intention can be evaluated by assessing healthcare professionals' willingness to use AI tools in future clinical practice, such as within the next month or clinical rotation. [52,54]

(iii) Socio-technical and governance perspective: why intention may not become utilisation

Healthcare AI adoption literature consistently shows that intention to use can be high while actual utilisation remains low due to system-level barriers. The 2024 scoping review on AI adoption barriers and facilitators emphasised organisational readiness, governance, trust, data quality, and integration into clinical workflows.[49] Likewise, work on Nigerian clinicians' early perspectives on LLMs points to operational barriers and privacy concerns as real constraints even when interest is present.[46] These perspectives explain the "intention–behaviour gap" that is especially relevant in Nigerian tertiary hospitals.

This is where ethics and governance theory matters: the WHO's 2021 guidance frames ethical governance (human oversight, accountability, transparency, and data protection) as foundational to safe adoption.[48] In practical terms, UBTH utilisation will likely be higher where there are clear rules on data handling, permitted tools, documentation expectations, and responsibility for AI-assisted outputs.

Together, these theories explain AI adoption as a layered process. At the cognitive level, knowledge influences healthcare professionals' expectations of AI as well as their awareness of potential risks. At the attitudinal level, factors such as perceived usefulness, ease of use, trust, and perceived risk shape acceptance of AI technologies. The behavioural layer reflects the actual uptake of AI tools when opportunities for use are available within clinical practice. Finally, at the system level, sustained utilisation depends on the presence of facilitating conditions, institutional support, infrastructure, and appropriate governance frameworks. [48,49,52,54]

2.3 CONCEPTUAL FRAMEWORK

This study's conceptual framework explains how knowledge and attitude shape uptake and level of utilisation of AI in clinical assessment among UBTH healthcare professionals, while recognising that adoption is constrained or enabled by individual, organisational, and environmental factors.

Core constructs and outcome pathways

Knowledge of AI in clinical support refers to healthcare professionals' awareness and understanding of AI tools used for clinical decision support, documentation assistance, diagnostic support, triage, risk prediction, and workflow optimization.[3,28] This includes familiarity with basic AI concepts, awareness of the local availability of AI-enabled tools, understanding of their capabilities and limitations, and recognition of associated risks such as bias, privacy concerns, and error propagation.[48,49] Good knowledge is expected to increase the likelihood of experimentation with AI tools and promote broader and more sustainable utilisation in clinical practice.[28,31]

Attitude toward AI use refers to the positive or negative disposition of healthcare professionals regarding the use of AI tools in healthcare. This includes perceptions of usefulness, safety, professionalism, and ethical acceptability of AI-assisted clinical practice.(31,36) Attitudes are influenced by factors such as perceived reliability, trust in AI systems, and perceived risks associated with their use.(37,51) More positive attitudes are expected to predict greater uptake and higher levels of utilisation intensity.

Uptake of AI for clinical support, defined as whether a healthcare professional has ever used an AI tool for any clinical-support purpose, represents the first threshold of adoption. It reflects the initial decision to try or adopt AI technologies in practice and is often influenced by social influence, availability of AI tools, and opportunities for use within the clinical environment.(36,37) However, while uptake is necessary for adoption, it alone is not sufficient to ensure sustained use over time.

Level of utilisation refers to the extent and intensity of AI use in clinical practice, including the degree to which AI is integrated into routine tasks and the range of functions for which it is used to support clinical care. (37,49) A healthcare professional may demonstrate uptake of AI tools but still have a low level of utilisation due to inadequate infrastructure, limited trust in AI systems, or poor integration into existing workflows. (49,51)

Determinant domains (influencing factors)

Concerning influencing factors, the concept is operationalised across five major domains, consistent with socio-technical evidence on AI adoption in healthcare settings. (49,50)

Individual factors include characteristics such as profession or cadre, years of clinical experience, and level of involvement in clinical decision-making, all of which may influence both exposure to AI technologies and the perceived relevance of these tools in practice. (28,32) In addition, digital literacy, prior exposure to AI or related training, and personal innovativeness may shape healthcare professionals' willingness to experiment with and continue using AI tools. [52]

Technology-related factors focus on the characteristics of the AI systems themselves. Perceived usefulness and perceived ease-of-use, particularly the extent to which the technology is viewed as beneficial and effortless to use, are important determinants of both adoption and sustained utilisation.[36,53] Other tool characteristics, including explainability, accuracy, transparency, and perceived risk, may influence trust in AI systems and consequently affect their utilisation. [51,52]

Organisational factors relate to the institutional environment in which healthcare professionals operate. The availability of digital devices, internet connectivity, stable electricity supply, IT support, and leadership endorsement may determine whether initial uptake of AI can progress into routine clinical utilisation. [49] Furthermore, the presence of structured training programmes, standard operating procedures, and supportive supervision may strengthen utilisation while reducing anxiety associated with AI use. [49,52]

Policy, ethics, and governance factors also play an important role in shaping AI adoption. Privacy safeguards, accountability mechanisms, and clear institutional guidance regarding responsible AI use influence healthcare professionals' comfort and confidence in using AI within clinical settings. [48,50] Professionals may be reluctant to use AI tools if there is uncertainty regarding medico-legal responsibility, data protection, or institutional policies governing AI use. [48,49]

Environmental and contextual factors include broader external influences such as national digital health policies, the availability of technology vendors, and prevailing professional norms, all of which may either accelerate or hinder AI adoption within healthcare systems. [49,50]

Mediators and moderators

Trust functions as an important mediator within the adoption process. Greater knowledge of AI may improve trust by increasing understanding of the technology's capabilities and limitations, whereas negative experiences with AI systems may reduce trust and subsequently lower utilisation even after initial uptake.(51) In addition, facilitating conditions such as infrastructure, training opportunities, and IT support may moderate the pathways between knowledge and uptake, as well as between attitude and sustained utilisation.(49,52)

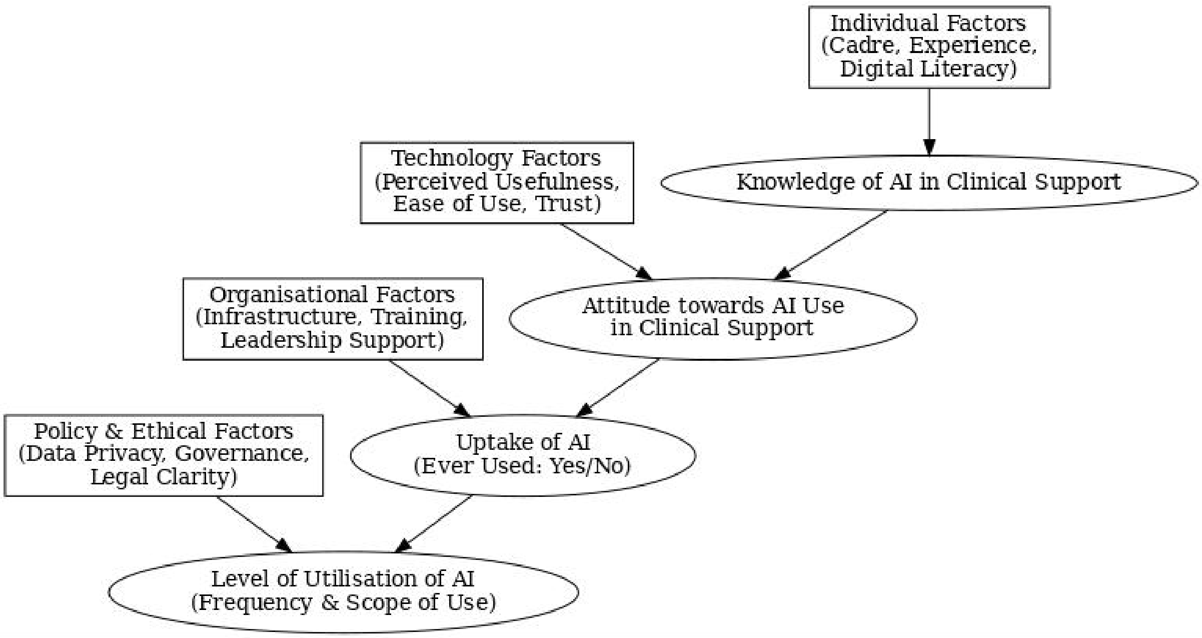

Figure 2.1: Conceptual framework of study

2.4 KNOWLEDGE OF ARTIFICIAL INTELLIGENCE

A cross-sectional online survey was conducted in Syria from April to May 2022 to assess the knowledge, attitude, and practice of artificial intelligence (AI) among doctors and medical students. A total of 1,494 participants, including 255 doctors and 1,252 medical students, were sampled using a convenience sampling technique, and data were collected through an online questionnaire. The study revealed that while 70% of participants had prior knowledge of AI, only 23.7% understood its medical applications. It is important to note that this study had some limitations. Data collection was conducted via social media platforms, which may have introduced selection bias, and responses were self-reported, increasing the possibility of inaccuracies. Additionally, the study was limited to Syrian medical professionals, affecting the generalizability of the findings to other regions.[31]

A cross-sectional survey was conducted among German surgeons from April to December 2021 to assess their knowledge, attitudes, and perspectives on artificial intelligence (AI) in surgical practice. A total of 147 surgeons from university hospitals, academic teaching hospitals, and private practices participated in the anonymous survey, which was distributed via email. The study revealed that while 52.8% of participants were familiar with AI applications in medicine, only 44.1% were aware of its use in their specialty, and most self-rated their knowledge as average or below average. It is important to note that this study had some limitations. The sample consisted mainly of surgeons from university hospitals, making the findings less generalizable to non-academic settings, and the self-reported nature of the data may have introduced bias. [32]

A cross-sectional study was conducted in Mogadishu, Somalia, from January to March 2024 to assess the knowledge, attitudes, and practices of artificial intelligence (AI) among healthcare professionals. A total of 441 participants were sampled using an online questionnaire distributed via social media and in-person hospital visits. Most respondents demonstrated good knowledge of AI, with 67.6% scoring above 60% on the knowledge assessment. Over 74% recognized AI's potential in diagnosis, treatment, research, education, and healthcare management. However, awareness of AI's ethical considerations and limitations was lower, with 66.7% identifying issues such as informed consent, accountability, and transparency, while 69.8% recognized concerns related to data quality, privacy, security, bias, and errors. It is important to note that this study had some limitations. The reliance on self-reported data and online distribution may have introduced response bias, and the study was conducted in a single city, limiting the generalizability of the findings to other regions of Somalia or similar low-resource settings.[33]

A cross-sectional study was conducted among physicians in Sudan to assess their knowledge, attitudes, and practices regarding artificial intelligence (AI) in medicine. A total of 1,007 physicians participated in the study, with data collected through an online questionnaire. The study revealed that while 80.7% of participants were aware of AI, however only 30.5% had good knowledge of AI use in clinical practice. It is important to note that this study had some limitations. The use of an online questionnaire may have introduced selection bias, as those with prior interest in AI were more likely to participate, and the self-reported nature of the responses may have affected accuracy. Additionally, the study was limited to Sudanese physicians, which may affect the generalizability of the findings to other regions.[34]

A descriptive cross-sectional study was conducted among staff of Federal Medical Centre Makurdi, Benue State, Nigeria, from March to May 2023 to assess their knowledge, practice, perception, and expectations regarding AI in medical care. A total of 384 respondents were sampled using a convenience sampling technique, and data were collected through self-administered questionnaires. The study revealed that although 69% of respondents were aware of AI, while only 12.5% had in-depth knowledge. It is important to note that this study had some limitations. The convenience sampling technique used may not represent the broader population, and the respondents' self-reported knowledge may not accurately reflect their true understanding of AI. Therefore, the findings should be interpreted with caution.[35]

A descriptive cross-sectional study was conducted among medical practitioners in two tertiary institutions in Port Harcourt, South-South Nigeria, over a period of 8 months to evaluate the knowledge, practice, and perception of AI in healthcare. A total of 510 questionnaires out of 525 administered were retrieved and analyzed using SPSS version 21.0. The study revealed that 94.31% of respondents had heard of AI, with the internet being the primary source of information (89.32%). However, only 29.67% had heard of deep machine learning, and knowledge of AI applications in pathology, drug-dispensing, and nursing care was limited. It is important to note that this study had some limitations. The lack of formal or informal training on AI and the absence of AI practice in the study environment may have influenced the respondents' knowledge and perception. Additionally, poor knowledge of information technology and the absence of legislation and control over AI applications were identified as challenges. Therefore, the findings should be interpreted with caution.(2)

2.5 ATTITUDE TOWARDS THE USE OF ARTIFICIAL INTELLIGENCE

A qualitative interview study was conducted between March and May 2020 in Germany to explore general practitioners' (GPs) attitudes toward artificial intelligence (AI)–enabled systems in medical diagnosis. A total of 18 GPs were interviewed, and data were analyzed using grounded theory to identify key determinants shaping their perspectives. The study revealed five major categories influencing GP attitudes: concerns, expectations, environmental influences, individual characteristics, and minimum requirements for AI use. While GPs acknowledged AI's potential to enhance diagnostic accuracy and efficiency, concerns over loss of professional autonomy, data security, and impact on physician-patient relationships were prominent. It is important to note that this study had some limitations. The small sample size and focus on German GPs limit the generalizability of the findings to broader healthcare settings, and the qualitative approach may not capture the full diversity of opinions on AI in primary care.(36)

A cross-sectional survey was conducted between July and November 2021 in two Dutch academic intensive care units (ICUs) to assess physicians' perspectives on artificial intelligence–based clinical decision support (AI-CDS) tools. A total of 64 ICU physicians participated in the study, and data were collected through a structured questionnaire covering decision-making behavior, attitudes towards AI, and willingness to integrate an AI-CDS tool for predicting ICU discharge outcomes. 86% of respondents believed AI could support their clinical work. Additionally, 92% agreed that an AI-CDS tool could provide value in discharge decisions, though concerns about transparency and explainability remained. It is important to note that this study had some limitations. The sample was drawn from only two academic ICUs, limiting the generalizability to non-academic hospitals, and the study relied on self-reported data, which may have introduced response bias.[(37)]

A cross-sectional study was conducted in Mogadishu, Somalia, from January to March 2024 to assess healthcare professionals' knowledge, attitudes, and practices regarding artificial intelligence (AI) in healthcare. A total of 441 participants were sampled through an online and in-person questionnaire. The study revealed that 80.5% of respondents had a positive attitude towards AI, recognizing its potential to enhance accessibility, reduce workloads, and optimize resources. However, concerns about AI replacing human doctors, ethical considerations, and the need for regulation persisted. It is important to note that this study had some limitations. The reliance on self-reported data may have introduced response bias, and the study was limited to one city, restricting the generalizability of the findings to other regions.[(33)]

A cross-sectional study was conducted in 2024 among physicians in Sudan to assess their knowledge, attitudes, and practices regarding artificial intelligence (AI) in medicine. A total of 825 physicians participated in the study, with data collected through an online questionnaire. The study revealed that 81.8% of participants believed AI is important in medicine, and 82.6% supported incorporating AI education into medical school curricula. Additionally, 78.9% expressed interest in working with AI in the future. However, concerns persisted, with 32% fearing AI could replace physicians and 42.9% worried about AI-induced diagnostic errors. It is important to note that this study had some limitations. The use of an online questionnaire may have introduced selection bias, as those with prior interest in AI were more likely to participate, and the study was limited to Sudanese physicians, which may affect the generalizability of the findings to other regions.(34)

A cross-sectional study was conducted in 2023 to assess the knowledge and perception of healthcare workers regarding the adoption of artificial intelligence (AI) in healthcare service delivery in Nigeria. A total of 263 healthcare professionals, including medical doctors, radiographers, and nurses, participated in the survey, with data collected via electronic and hardcopy questionnaires. 78.7% of respondents agreed that AI could help reduce medical errors, and 61% believed AI could be applied to all medical specialties. However, 29.3% of respondents feared that human specialists might be replaced by AI in the future, and 40.3% believed some employers would prefer AI due to its lack of emotional exhaustion or physical limitations. It is important to note that this study had some limitations. The use of self-reported data may have introduced response bias, and the study was conducted in a single country, which may limit the generalizability of the findings to other regions.(9)

A cross-sectional study was conducted in 2023 across six geopolitical zones in Nigeria to assess the knowledge and perception of healthcare professionals regarding artificial intelligence (AI) and machine learning in healthcare. A total of 404 participants, including physicians, pharmacists, and nurses, were sampled using a stratified multistage sampling method, and data were collected through a questionnaire. The study revealed that 66.7% of respondents believed AI would augment human intelligence rather than replace healthcare professionals, while 57.8% disagreed with the notion that AI adoption would lead to job losses. Additionally, 77% agreed that AI could facilitate efficient healthcare service delivery, though concerns remained regarding ethical challenges (68.7%) and the cost of AI-driven healthcare services (61.2%). It is important to note that this study had some limitations. The use of self-reported questionnaires may have introduced response bias, and the study's focus on Nigerian healthcare professionals limits the generalizability of the findings to other regions.[28]

2.6 UPTAKE AND LEVEL OF USAGE OF ARTIFICIAL INTELLIGENCE

A narrative review was conducted in 2024 to examine the level of usage of ChatGPT in the medical field. The study analyzed existing literature on ChatGPT's application in clinical practice, healthcare, medical education, and research. It revealed that while ChatGPT is increasingly being explored for clinical decision support, patient consultations, and medical documentation. The review highlighted that although many doctors recognize ChatGPT's potential, its adoption in real-world medical settings is still in its early stages, with most applications being experimental rather than fully integrated into clinical workflows. It is important to note that this study had some limitations. The review relied on existing literature, which may not fully reflect the most recent advancements in AI adoption, and most of the reviewed studies were conducted in developed countries, limiting the generalizability of findings to low-resource healthcare settings .[38]

A scoping review was conducted in 2022 to examine how artificial intelligence (AI) is being implemented in healthcare practice. A total of 45 studies were analyzed, covering various clinical settings and disciplines, primarily from high-income countries (73%). The study revealed that AI systems are predominantly used for clinical care, especially in patient-provider interactions, with 53% of AI tools functioning as decision support systems rather than autonomous applications. However, the research found that actual AI implementation in routine practice remains limited, with most studies focusing on technical development rather than real-world adoption. It is important to note that this study had some limitations. The review primarily included studies from high-income settings, limiting the generalizability of findings to resource-constrained regions, and there was a lack of standard implementation frameworks, making it difficult to assess best practices for AI integration.[39]

A scoping review was conducted in 2023 to assess the use of artificial intelligence (AI) in delivering essential health services across WHO regions. The study analyzed various AI applications in disease detection, diagnosis, classification, management, and treatment across different healthcare settings. The findings revealed that AI is widely used in high-income countries, particularly for managing communicable and non-communicable diseases, but its adoption remains limited in low- and middle-income countries (LMICs), including Africa. It is important to note that this study had some limitations. The review was based on existing literature, which may not fully capture the latest AI implementations, and most of the included studies focused on high-income regions, limiting the generalizability of the findings to resource-constrained healthcare systems.[40]

A review study was conducted in 2024 to assess the level of artificial intelligence (AI) usage in healthcare advancements across Africa. The study explored AI applications in diagnostics, telehealth, and public health monitoring, highlighting successes in AI-powered disease detection, virtual patient consultations, and epidemic response systems. While AI has shown promise in malaria diagnostics, pneumonia detection, and remote patient monitoring, its real-world implementation remains low. Many AI-based healthcare solutions are still in pilot stages rather than fully integrated into national health systems. It is important to note that this study had some limitations. The review relied on existing literature, which may not fully capture the most recent AI deployments, and most studies focused on high-income regions, limiting their generalizability to resource-constrained settings .[41]

A 2025 narrative review study examined the role of artificial intelligence (AI) in healthcare advancement in Nigeria and highlighted its applications in disease diagnosis, personalized medicine, drug discovery, epidemiological surveillance, and healthcare management. The review reported that AI technologies such as deep learning and machine learning have been applied in medical imaging, genomics research, predictive analytics, electronic health record management, and disease outbreak forecasting to improve diagnostic accuracy, healthcare efficiency, and clinical decision-making. The study further noted that AI has the potential to enhance telemedicine services, optimize healthcare resource allocation, and strengthen evidence-based healthcare delivery in resource-limited settings. The review also observed that many AI-driven healthcare innovations in Nigeria are still largely confined to pilot studies and experimental settings rather than routine clinical practice. It is important to note that this review had some limitations. The findings were based mainly on existing literature and secondary data sources, which may not accurately reflect the actual level of AI implementation in Nigeria, while most available evidence originated from high-income countries, thereby limiting the generalizability of the findings to Nigeria's healthcare system..(42)

A 2024 cross-sectional study was conducted at the University of Uyo Teaching Hospital (UUTH), Nigeria, to assess the knowledge, perception, and use of artificial intelligence (AI) among healthcare workers. A total of 227 healthcare professionals, including doctors, nurses, pharmacists, physiotherapists, and medical laboratory scientists, participated in the study through a stratified random sampling technique. The study revealed that only 7.9% reported using AI in their departments, with 67.4% stating they did not use AI in their activities. Personal AI usage was also low, with 32.6% of respondents using AI, mainly for studying and research (54.1%). It is important to note that this study had some limitations. The findings were based on self-reported data, which may have introduced response bias, and the study was conducted at a single institution, limiting the generalizability of the results to other healthcare settings in Nigeria.(29)

2.7 FACTORS INFLUENCING THE USE OF ARTIFICIAL INTELLIGENCE

A 2022 qualitative interview study conducted in Germany examined the factors influencing the adoption of human-AI collaboration in clinical decision-making. Through semi-structured interviews with healthcare professionals specializing in radiology, pulmonology, pathology, and AI, the study identified six key factors affecting AI adoption: complementarity, mutual learning, user adaptiveness, decision transparency, time efficiency, and human agency. While medical professionals recognized AI's ability to enhance clinical workflows, concerns over the lack of explainability, workflow integration challenges, and trust in AI recommendations hindered widespread adoption. It is important to note that this study had some limitations. The research relied on a small sample size (10 experts), which may not fully represent the views of a broader medical community, and findings were based on qualitative interviews, limiting the ability to quantify the significance of each factor.[(43)]

A 2024 scoping review was conducted by researchers at the University of Victoria, Canada, to examine the barriers to and facilitators of artificial intelligence (AI) adoption in healthcare. The study analyzed 50 articles published between 2011 and 2023 to identify key factors influencing AI adoption. The findings revealed 18 major barriers and facilitators, including trust, regulatory and legal frameworks, governance structures, data security concerns, and workflow integration challenges. Trust was identified as a critical factor, impacted by issues such as lack of explainability, algorithm bias, and ethical concerns. The study emphasized the need for strong governance models and regulatory policies to improve AI adoption. It is important to note that this study had some limitations. The review was based on existing literature, which may not fully capture the most recent AI developments, and most of the reviewed studies focused on high-income countries, limiting the generalizability of findings to low-resource healthcare settings.[(44)]

A 2025 commentary published in Health Affairs Scholar examined the factors influencing artificial intelligence (AI) adoption in healthcare across Sub-Saharan Africa. The study identified infrastructure deficits, lack of structured health data, biases in AI models, brain drain, financial constraints, and geopolitical dynamics as key barriers to AI implementation. The limited availability of high-quality local data prevents AI models from being effectively trained for African healthcare needs, while biases in Western-developed algorithms pose risks of inaccurate diagnoses. Additionally, only 28% of the Sub-Saharan population has regular internet access, further limiting AI-based healthcare solutions. The study emphasized that economic dependency on foreign AI technologies exacerbates inequalities, restricting local innovation. It is important to note that this study had some limitations. As a commentary piece, it relied on secondary data rather than empirical research, and its broad focus on Sub-Saharan Africa limits the ability to draw country-specific conclusions.[45]

A 2024 review article was conducted to assess the integration of artificial intelligence (AI) in the sub-Saharan African health sector, focusing on its impact, current applications, challenges, and potential future advancements. This article highlighted the major barriers behind AI use in aspects such as mobile-based diagnostics, disease prediction and detection, were identified, and they included infrastructure deficits, data privacy concerns, and a lack of digital skills among healthcare professionals. It is important to note that this study had some limitations. The review primarily relied on secondary data sources, which may not reflect the full scope of AI implementation in healthcare across the region. Additionally, findings were generalized for sub-Saharan Africa, which comprises diverse healthcare systems and challenges, potentially limiting the applicability of conclusions to specific contexts.[30]

A 2024 cross-sectional survey was conducted in Nigeria to assess medical doctors' early perspectives, operational barriers, and privacy concerns regarding large language models

(LLMs) like ChatGPT in healthcare. The study involved 406 medical doctors across Nigeria's six geopolitical zones, with data collected via an online questionnaire. Key factors influencing AI adoption included concerns about misinterpretation (80.1%), overreliance on technology (66.3%), liability issues (65.5%), lack of human interaction (60.7%), and data privacy concerns (51.3%). It is important to note that this study had some limitations. The use of an online questionnaire may have introduced selection bias, and findings were based on self-reported data, which may not accurately reflect real-world AI adoption.[46]

A 2023 qualitative multi-case study was conducted among five hospitals in Nigeria to explore strategies employed by healthcare leaders for the successful adoption and implementation of Artificial Intelligence (AI)-based medical device technologies. The study involved in-depth interviews with 11 healthcare leaders from these hospitals. It revealed that a mix of implementation strategies, including financial planning, vendor selection processes, maintenance agreements, staff training, and governmental financial support, were critical to obtaining and deploying AI technologies. erratic power supply and inadequate maintenance resources were key barriers to implementation, while collaborative efforts, such as leveraging manufacturers' local repair centers, emerged as solutions. The findings identified the complexity of diseases, patient load, and competition in the healthcare industry as major factors influencing the adoption of AI medical devices. Clinicians acknowledged that these technologies enhanced diagnostic accuracy, reduced medical errors, increased referrals, shortened hospital stays, and improved overall operational efficiency. It is important to note that this study had some limitations. The study focused on a small sample size and lacked insights into public healthcare systems, potentially limiting the generalizability of the findings across all healthcare providers in Nigeria. However, the study offers a framework for addressing barriers and implementing AI-based technologies in resource-limited settings. [47]

CHAPTER THREE

METHODOLOGY

3.1 STUDY AREA

This study was conducted at the University of Benin Teaching Hospital (UBTH), located in Benin City, Edo State, Nigeria. Edo State is one of the 36 states in Nigeria and lies within the South–South geopolitical zone of the country. The state was created on 27 August 1991 from the northern part of the former Bendel State and has Benin City as its capital. Edo State shares boundaries with Kogi State to the northeast, Anambra State to the east, Delta State to the southeast, and Ondo State to the west and northwest.[57]

Benin City is a humid tropical urban settlement comprising three Local Government Areas: Egor, Ikpoba Okha, and Oredo. Geographically, Benin City is described as a narrow, key-shaped, north–south strip of land in West Africa, covering an estimated land area of about 1,125 km^2. The terrain is relatively flat, with an elevation of approximately 80m above sea level, and it lies between latitude 6°44′N and 6°21′N and longitude 5°35′E and 5°44′E. The population of Edo State is projected to reach approximately 5.42 million by 2025, with an average annual growth rate of about 3.2%, comprising roughly 2,550,240 males and 2,869,760 females. The state is ethnically diverse, with the Binis constituting about 57.5% of the population, followed by the Esan (14.1%), Etsako (12.2%), Owan (7.4%), and Akoko Edo (5.7%), alongside other minority ethnic groups.[58]

The University of Benin Teaching Hospital is a federal tertiary health institution established on 12 May 1973 following the enactment of Edict No. 12 in April 1971. The hospital was created to support the University of Benin and to provide secondary and tertiary healthcare services to the then Midwestern Region, now comprising Edo and Delta States. On 1 April 1975, UBTH was taken over by the Federal Government, making it the fifth teaching hospital in Nigeria at that time. Over the past four decades, UBTH has functioned as a major referral centre for complex medical and surgical conditions. Its catchment areas include Edo State, Delta State, parts of Kogi and Ondo States, and occasionally other parts of southern Nigeria.[59]

Originally commissioned as a 300-bed facility, UBTH has expanded significantly and currently operates with a bed capacity exceeding 900. The hospital is located in Egor Local Government Area along the Benin–Ore Road and shares boundaries with the University of Benin and the Federal Government Girls' College Road.[59]

UBTH is a multi-specialist tertiary institution with a wide range of clinical departments involved in healthcare delivery, medical education, and research. These include Internal Medicine, Surgery, Chemical Pathology, Haematology, Histopathology, and Medical Microbiology, as well as subspecialties such as Orthopaedics, Dermatology, Radiology, Anaesthesiology, Family Medicine, Ear, Nose and Throat (ENT), and Ophthalmology. Other core departments include Child Health, Obstetrics and Gynaecology, Public Health, Mental Health, and Dentistry. In addition, UBTH houses the College of Nursing and departments of Physiotherapy, Occupational Therapy, and Pharmacy, which collectively support the hospital's mandate of providing high-quality patient care, training healthcare professionals, and advancing medical research in Nigeria. [59]

3.2 STUDY DESIGN

An analytical cross-sectional study design was utilised in this study.

3.3 STUDY DURATION

The study was conducted between December 2024 and May 2026.

3.4 STUDY POPULATION

The study was carried out among healthcare workers at the University of Benin Teaching Hospital (UBTH), Benin City, Edo State, Nigeria. These included medical doctors, nurses, pharmacists, laboratory scientists and physiotherapists. These professionals are involved in clinical care and clinical decision-making. Both senior and junior healthcare workers across relevant clinical departments were eligible to participate in the study.

3.5 SELECTION CRITERIA

3.5.1 Inclusion criteria

I. Health workers working in UBTH.

II. Health workers who gave consent for the study.

III. Health workers involved in patient care, such as doctors, nurses, pharmacists, laboratory scientists, and physiotherapists.

3.5.2 Exclusion Criteria

I. Health workers who declined or were too busy to respond.

II. Health workers who were on leave, secondment, prolonged posting outside UBTH, or otherwise unavailable throughout data collection.

3.6 SAMPLE SIZE ESTIMATION

The minimum sample size (n) was calculated using the Cochran's formula used for descriptive studies.[60]

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

Where,

n = minimum sample size

Z = standard normal deviate = 1.96 at 95% confidence interval

p = prevalence of the characteristic of interest

q = 1-p

d = degree of precision desired set at 0.05

The value of p was set at 86.5%, based on the prevalence of AI use reported in a cross-sectional study carried out in Lagos, Nigeria to assess the prevalence, patterns, and determinants of artificial intelligence use among healthcare professionals. [61]

p = 0.865

q = 1 p = 1-0.865 = 0.135

d = Degree of precision set at 0.05 Confidence interval

Hence:

$$n = \frac{(1.96)^2 \times (0.865) \times (0.135)}{(0.05)^2}$$

n= 179

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

$$nf = \frac{n}{1 - nr}$$

n = Minimum sample size = 179

nr = non-response rate = 10% = 0.10

nf = Final minimum sample size

$$= \frac{179}{1\text{-}0.10} = \frac{179}{0.90} = 199$$

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

= 199 x 2= 398

Thus, the final minimum sample size for this study was 398. However, a final sample size of 409 was used for this study.

3.7 SAMPLING TECHNIQUE

A multi-stage sampling technique was employed to select participants for the study, ensuring adequate representation of healthcare professionals across different professional cadres at the University of Benin Teaching Hospital.

Stage 1: Selection of facility

The study was conducted at the University of Benin Teaching Hospital. UBTH was purposively selected because it is a federal tertiary teaching hospital with a diverse healthcare workforce and a gradually evolving digital health infrastructure, making it suitable for assessing the uptake and level of utilisation of AI in clinical support.

Stage 2: Selection of Professional Cadres

The study population comprised healthcare professionals directly involved in clinical and clinical-support services at UBTH. Five professional cadres were included in the study, namely doctors, nurses, pharmacists, medical laboratory scientists, and physiotherapists. These cadres were included through total enumeration at the stratum level, as they represent the core clinical and allied health professionals most relevant to AI-supported clinical activities.

Stage 3: Proportionate Allocation of Sample Size by Cadre

The sample size was distributed across the selected professional cadres using proportionate allocation, based on staff strength obtained from the UBTH Human Resources Department. The total eligible population of healthcare professionals was 1,551, comprising 617 doctors, 744 nurses, 68 pharmacists, 89 medical laboratory scientists, and 33 physiotherapists. The final sample size for the study was 398.

Proportionate allocation was determined using the formula:

$$n_h = \frac{N_h}{N} \times n$$

where:

n_h= allocated sample size for each cadre

N_h= population of each cadre

N= total population

n= total sample size

Cadre	**Estimated Population**	**Proportion (N_h/N)**	**Allocated Sample**	**Final Allocation**
Doctors	617	0.398	158.33	**158**
Nurses	744	0.480	190.92	**191**
Pharmacists	68	0.044	17.45	**17**
Medical Laboratory Scientists	89	0.057	22.84	**23**
Physiotherapists	33	0.021	8.47	**9**
Total	**1,551**	**1.000**		**398**

Thus, the proportional allocation yielded 158 doctors, 191 nurses, 17 pharmacists, 23 medical laboratory scientists, and 9 physiotherapists.

Stage 4: Selection of Respondents

Within each professional cadre, systematic random sampling was applied to select respondents. The sampling frame consisted of nominal staff lists obtained from the UBTH Human Resources Department, arranged alphabetically by surname. The sampling interval (k) was calculated for each cadre by dividing the cadre population by the allocated sample size. A random starting point between 1 and k was selected by balloting, after which every k^{th}eligible staff member on the list was selected until the required sample size for each cadre was achieved.

Where a selected participant was unavailable, ineligible, or declined consent, the next eligible staff member on the list was approached to maintain the sampling interval and achieve the allocated sample size.

3.8 Data Management

3.8.1 Tools for Data Collection

Data were collected using a structured, self-administered questionnaire adapted from validated instruments used in previous studies in Nigeria, Syria and Germany on artificial intelligence (AI) among healthcare professionals.[1,31,36]

3.8.2 Sections of the Questionnaire

The questionnaire comprised five main sections, structured in line with the specific objectives:

Section A: Sociodemographic Data; This section collected information on age, sex, professional cadre, years of practice, highest educational qualification, department/unit, and monthly income.

Section B: Knowledge of Artificial Intelligence in Clinical Assessment; This section assessed respondents' understanding of AI, including basic concepts, areas of application in clinical support, perceived capabilities and limitations, and awareness of AI tools relevant to healthcare practice. Items were structured as single-best-answer and a few multiple response questions to ensure clarity.

Section C: Attitudes Toward the Use of Artificial Intelligence in Clinical Assessment; This section measured respondents' beliefs, perceptions, and acceptance of AI use in clinical assessment, and a 5-point Likert scale ranging from Strongly Disagree to Strongly Agree was used.

Section D: Uptake and Level of Utilisation of Artificial Intelligence; This section assessed whether respondents had ever used AI in clinical support (uptake), as well as the frequency, scope, and context of use (level of utilisation), including clinical decision support, documentation, diagnostics, and workflow assistance.

Section E: Factors Influencing Uptake and Utilisation of Artificial Intelligence; This section explored individual, organisational, technological, and policy-related factors influencing AI adoption, including availability of infrastructure, training, institutional support, perceived risks, data privacy concerns, and workload considerations. Items were structured mainly as yes/no questions to facilitate analysis.

3.8.3 Method of Data Collection

Data collection was carried out over a four-week period. Questionnaires were administered to eligible healthcare professionals within the hospital premises in locations that ensured privacy and minimal disruption to clinical duties. Participants were provided with a clear explanation of the study objectives, and informed consent was obtained prior to participation. Participation was voluntary, and respondents were assured that all information provided would remain anonymous and confidential.

3.8.4 Research Assistants

No research assistants were employed for this study. The administration of the questionnaires, data collation, and data analysis were entirely carried out by the researchers.

3.9 Data Analysis

Data collected were cleaned, then entered, and analysed using IBM Statistical Package for the Social Sciences (SPSS) version 27.0. Data analysis involved:

- **Descriptive statistics**, including frequencies, percentages, means, and standard deviations, to summarise socio-demographic characteristics and responses to questionnaire items.
- **Inferential statistics**, including chi-square tests, fisher's exact test and logistic regression analysis, to examine associations between socio-demographic variables, knowledge, attitudes, uptake, and level of utilisation of artificial intelligence in clinical support.

A p-value of less than 0.050 was considered statistically significant.

Scoring System

Knowledge of Artificial Intelligence in Clinical Assessment

A total of 20 questions assessed respondents' knowledge of artificial intelligence in clinical assessment. Each correct answer was scored as 1 point, while each incorrect answer was scored as 0 points.

The total knowledge score was calculated and converted into a percentage of the maximum obtainable score. Knowledge was interpreted as follows:

- **0%–69.9%:** Poor knowledge
- **70%–100%:** Good knowledge[1]

Attitude Towards the Use of Artificial Intelligence in Clinical Assessment

Respondents' attitudes toward the use of AI in clinical support were assessed using ten questions measured on a 5-point Likert scale: Strongly agree, Agree, Neutral, Disagree, and Strongly disagree.

Negatively worded statements were reverse scored to ensure consistency in directionality. Each appropriate response was given a score of 1, an inappropriate response was given a score of 0 and neutral responses were also scored as 0. The total attitude score was summed and converted into a percentage of the maximum obtainable score.

Attitude was interpreted as follows:

- **0%–69.9%:** Negative attitude
- **70%–100%:** Positive attitude [31]

Uptake and Level of Utilisation of Artificial Intelligence

Uptake of artificial intelligence was assessed using respondents' self-reported ever use of any AI-based tool in clinical assessment. Respondents were categorised as having ever used AI or as never having used AI.

Level of utilisation was assessed using the frequency of AI use. Responses were coded and categorised as follows:

- **Never/Rarely/ Monthly:** Low utilisation
- **Weekly/Daily/Almost daily:** High utilisation

These measures were analysed descriptively and used to determine patterns and intensity of AI utilisation among healthcare professionals [31]

Factors Influencing Uptake and Utilisation of Artificial Intelligence

Factors influencing uptake and utilisation of AI were assessed using 11 questions. These included training, infrastructure availability, institutional support, workload, data privacy concerns, legal and ethical considerations, peer influence, cost, and policy environment.

These variables were analysed for their association with level of utilisation of AI using inferential statistical methods such as chi-square tests. Fisher's exact test and logistic regression analysis. This approach enabled the identification of key predictors of AI uptake and utilisation among healthcare professionals.[52]

3.10 Data Presentation

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

3.11 Ethical Consideration

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/148654912797. Informed consent was obtained from all respondents before administering the questionnaires. Respondents were informed of their right to withdraw from the study at any point without any consequence or harm. The confidentiality and anonymity of the participants were maintained throughout the study. This study provided insight into current trends and challenges associated with AI use in clinical assessment among the healthcare professionals in UBTH and may help guide future training, policy formulation, and integration of AI technologies within the institution.

3.12 Study Limitation

The study relied on self-reported data, which may be subject to recall bias and social desirability bias. Additionally, given the evolving nature of artificial intelligence in healthcare, respondents' understanding and reporting of AI use may vary, potentially influencing responses.

CHAPTER FOUR
RESULTS

A total of 409 respondents participated in the study with 100% response rate. The results are presented in the following sections in line with the specific objectives.

SECTION A: Socio-demographic characteristics of healthcare professionals in UBTH

SECTION B: Knowledge of artificial intelligence in clinical assessment of healthcare professionals in UBTH

SECTION C: Attitude towards the use of artificial intelligence in clinical assessment among healthcare professionals in UBTH

SECTION D: Uptake and level of utilization of artificial intelligence in clinical assessment among healthcare professionals in UBTH

SECTION E: Factors influencing uptake and utilisation of AI in clinical assessment among healthcare professionals in UBTH

SECTION A:

SOCIO-DEMOGRAPHIC CHARACTERISTICS OF HEALTHCARE PROFESSIONALS IN UBTH

Table 1: Socio-demographic characteristics of respondents

Variables	Frequency (n = 409)	Percent
Age (Years)		
20–29	206	50.4
30–39	132	32.3
40–49	50	12.2
50–60	21	5.1
Mean ± SD	**31.78± 8.74**	
Sex		
Female	259	63.3
Male	150	36.7
Religion		
Christianity	398	97.3
Islam	11	2.7
Ethnicity		
Benin	151	36.9
Esan	75	18.3
Igbo	73	17.8
Estako	33	8.1
Yoruba	28	6.8
Urhobo	14	3.4
Ijaw	12	2.9
Isoko	7	1.7
Ibibio	6	1.5
Ebira	4	1.0
Owan	3	0.7
Others*	3	0.7
Marital Status		
Single	253	61.9
Married	145	35.5
Cohabiting	4	1.0
Divorced	4	1.0
Widowed	2	0.5
Separated	1	0.2
Occupation		
Nurse	194	47.4

Doctor	163	39.9
Medical Laboratory Scientist	22	5.4
Pharmacist	20	4.9
Physiotherapist	10	2.4
Department		
Nursing Services	194	47.4
Surgery	99	24.2
Medicine	64	15.6
Laboratory Services	22	5.4
Pharmaceutical Services	20	4.9
Physiotherapy	10	2.4
Staff Rank		
Junior Staff	228	55.7
Senior Staff	181	44.3
Years of Work Experience		
<10 years	349	85.3
≥10 years	60	14.7
Mean ± SD	**4.79± 5.07**	
Educational Qualification		
Bachelor's degree	299	73.1
Diploma (post-secondary)	33	8.1
Postgraduate diploma	30	7.3
Master's degree	30	7.3
Doctorate (PhD)	9	2.2
Fellowship	8	2.0

Others* are Igala 1(0.23%), Kamue 1(0.23%), Idoma 1(0.23%).

A total of 409 respondents participated in the study. Regarding age distribution, half of the respondents were aged 20–29 years (50.4%), followed by those aged 30–39 years (32.3%), 40–49 years (12.2%), and 50–60 years (5.1%). The majority were female (63.3%), while males accounted for 36.7%. Nearly all respondents were Christians (97.3%), with Muslims constituting 2.7%.

With respect to ethnic groups, Benin was the most represented (36.9%), followed by Esan (18.3%), Igbo (17.8%), Estako (8.1%), Yoruba (6.8%), Urhobo (3.4%). Regarding marital status, the majority were single (61.9%), followed by married respondents (35.5%), while cohabiting and divorced respondents each accounted for 1.0%, and widowed (0.5%) and separated (0.2%) respondents were the least represented.

In terms of occupation, nurses formed the largest group (47.4%), followed by doctors (39.9%), medical laboratory scientists (5.4%), pharmacists (4.9%), and physiotherapists (2.4%). Correspondingly, the largest proportion of respondents were from the Nursing Services department (47.4%), followed by Surgery (24.2%), Medicine (15.6%), Laboratory Services

(5.4%), Pharmaceutical Services (4.9%), and Physiotherapy (2.4%). Regarding staff rank, junior staff constituted the majority (55.7%), while senior staff accounted for 44.3%. Most respondents had less than 10 years of work experience (85.3%), with only 14.7% having 10 or more years.

With respect to educational qualification, the majority held a bachelor's degree (73.1%), followed by those with a Diploma (8.1%), Postgraduate diploma (7.3%), and Master's degree (7.3%), while Doctorate and Fellowship holders accounted for 2.2% and 2.0% respectively.

SECTION B:

KNOWLEDGE OF ARTIFICIAL INTELLIGENCE IN CLINICAL ASSESSMENT AMONG HEALTHCARE PROFESSIONALS IN UBTH

Table 2: Awareness and source of information about AI in clinical assessment among healthcare professionals in UBTH

Variables	Frequency (n = 409)	Percent
Have you heard of artificial intelligence (AI)	409	100.0
Source of Information*		
Internet	341	83.4
Social media	284	69.4
Colleagues	182	44.5
Television	178	43.5
Hospital Training	57	13.9
Journal	44	10.8
Radio	26	6.4

*** = Multiple response question**

All respondents (100.0%) had heard of Artificial Intelligence. Regarding sources of information, the internet was the most frequently reported source (83.4%), followed by social media (69.4%), colleagues (44.5%), and television (43.5%). Smaller proportions reported obtaining information through hospital training (13.9%), journals (10.8%), and radio (6.4%).

Table 3: Knowledge responses of AI in clinical assessment among healthcare professionals in UBTH

Variables	Frequency (n = 409)	Percent
Artificial intelligence refers to		
Computer systems that can perform tasks that normally require human intelligence	385	94.1
Automated machines that function independently without any human input or supervision	15	3.7
Internet communication systems	5	1.2
Machines that completely replace healthcare workers	3	0.7
Use of computers only for record keeping	1	0.2
Artificial intelligence can be used in healthcare to		
Support clinical decision-making	399	97.6
Eliminate human judgement	6	1.5
Replace doctors and nurses	3	0.7
Increase clinical errors	1	0.2
Which of the following are applications of AI in healthcare*		
Clinical Decision Support Systems (CDSS)	370	90.5
Medical Image Analysis	346	84.6
Predictive Risk Assessment	270	66.0
Paper-Based Records as AI	38	9.3
AI for Documentation	277	67.7
Which of the following AI tools used in clinical assessment are you familiar with*		
ChatGPT	388	94.9
Claude	66	16.1
Beta AI	48	11.7
Zoom	41	10.0
Stratify AI	20	4.9
Ada Health	16	3.9
Consensus AI	16	3.9
Qure AI	15	3.7
Sudoku AI	13	3.2
I don't know	7	1.7
What is a major benefit of AI in clinical assessment		
Improved accuracy and efficiency	408	99.8
Loss of patient safety	1	0.2
A known risk of AI use in healthcare is		
Bias in algorithms	381	93.2
Faster data processing	23	5.6
Improved workflow	3	0.7
Better documentation	2	0.5
For AI to be used safely in healthcare, there must be		
Ethical and regulatory guidelines	402	98.3
Complete vendor control	4	1.0
No human supervision	2	0.5
No data protection rules	1	0.2

*** = Multiple response question, Cronbach's alpha (α)= 0.718**

Regarding the definition of Artificial Intelligence, the majority of respondents (94.1%) correctly identified AI as computer systems that can perform tasks that normally require human intelligence, while smaller proportions incorrectly described it as automated machines that function independently without human input (3.7%), internet communication systems (1.2%), machines that completely replace healthcare workers (0.7%), or computers used only for record keeping (0.2%). When asked about the use of AI in healthcare, nearly all respondents (97.6%) correctly indicated that AI supports clinical decision-making, while 1.5% believed it eliminates human judgement, 0.7% thought it replaces doctors and nurses, and 0.2% indicated it increases clinical errors.

Concerning applications of AI in healthcare, Clinical Decision Support Systems (CDSS) was the most recognised application (90.5%), followed by Medical Image Analysis (84.6%), AI for Documentation (67.7%), and Predictive Risk Assessment (66.0%). A small proportion (9.3%) incorrectly identified Paper-Based Records as an AI application. Regarding familiarity with AI tools used in clinical assessment, ChatGPT was by far the most recognised tool (94.9%), followed by Claude (16.1%), Beta AI (11.7%), and Zoom (10.0%). Less familiar tools included Stratify AI (4.9%), Ada Health (3.9%), Consensus AI (3.9%), Qure AI (3.7%), and Sudoku AI (3.2%), while only 1.7% reported not knowing any of the listed tools.

With respect to the benefits of AI in clinical assessment, almost all respondents (99.8%) correctly identified improved accuracy and efficiency as a major benefit, while 0.2% incorrectly indicated loss of patient safety. Regarding known risks of AI use in healthcare, the majority (93.2%) correctly identified bias in algorithms as a major risk, while smaller proportions incorrectly selected faster data processing (5.6%), improved workflow (0.7%), and better documentation (0.5%).

Finally, regarding the conditions necessary for safe AI use in healthcare, 98.3% correctly indicated that ethical and regulatory guidelines are required, while 1.0% selected complete vendor control, 0.5% indicated no human supervision, and 0.2% suggested no data protection rules were needed.

Table 4: Correctness of knowledge responses of AI in clinical assessment among healthcare professionals in UBTH

Variables	Knowledge responses (n=409)	
	Correct (%)	**Incorrect (%)**
Artificial intelligence refers to		
Computer systems that can perform tasks that normally require human intelligence	385 (94.1)	24 (5.9)
Artificial intelligence can be used in healthcare to		
Support clinical decision-making	399 (97.6)	10 (2.4)
Which of the following are applications of AI in healthcare*		
Clinical Decision Support Systems (CDSS)	370 (90.5)	39 (9.5)
Medical Image Analysis	346 (84.6)	63 (15.4)
Predictive Risk Assessment	270 (66.0)	139 (34.0)
Paper-Based Records as AI	38 (9.3)	371 (90.7)
AI for Documentation	277 (67.7)	132 (32.3)
Which of the following AI tools used in clinical assessments are you familiar with*		
ChatGPT	388 (94.9)	21 (5.1)
Claude	66 (16.1)	343 (83.9)
Beta AI	361 (88.3)	48 (11.7)
Zoom	368 (90.0)	41 (10.0)
Stratify AI	20 (4.9)	389 (95.1)
Ada Health	16 (3.9)	393 (96.1)
Consensus AI	393 (96.1)	16 (3.9)
Qure AI	15 (3.7)	394 (96.3)
Sudoku AI	396 (96.8)	13 (3.2)
I don't know	402 (98.3)	7 (1.7)
What is a major benefit of AI in clinical assessment		
Improved accuracy and efficiency	408 (99.8)	1 (0.2)
A known risk of AI use in healthcare is		
Bias in algorithms	381 (93.2)	28 (6.8)
For AI to be used safely in healthcare, there must be		
Ethical and regulatory guidelines	402 (98.3)	7 (1.7)

*** = Multiple response question, α=0.718**

Regarding the definition of AI, 385 respondents (94.1%) provided the correct response, while 24 (5.9%) responded incorrectly. Nearly all respondents (97.6%) correctly identified that AI can be used in healthcare to support clinical decision-making, with only 10 (2.4%) responding incorrectly.

Concerning applications of AI in healthcare, Clinical Decision Support Systems was the most correctly identified application (90.5%), followed by Medical Image Analysis (84.6%), AI for Documentation (67.7%), and Predictive Risk Assessment (66.0%). Notably, the majority of respondents (90.7%) correctly identified that Paper-Based Records do not constitute an AI application, while 38 (9.3%) responded incorrectly, suggesting some residual gaps in conceptual understanding.

Regarding familiarity with AI tools used in clinical assessment, ChatGPT recorded the highest correct response rate (94.9%), while Claude (16.1%), Stratify AI (4.9%), Ada Health (3.9%), and Qure AI (3.7%) were far less recognised among respondents. For Beta AI, Zoom, Consensus AI, and Sudoku AI, which are not clinical assessment tools and the correct response was to not select them, most respondents demonstrated this ability, with correct response rates of 88.3%, 90.0%, 96.1%, and 96.8% respectively.

With respect to the major benefit of AI in clinical assessment, almost all respondents (99.8%) correctly identified improved accuracy and efficiency, with only one respondent (0.2%) responding incorrectly. Regarding known risks of AI use in healthcare, 381 respondents (93.2%) correctly identified bias in algorithms as a major risk, while 28 (6.8%) responded incorrectly.

Finally, regarding conditions necessary for safe AI use in healthcare, 402 respondents (98.3%) correctly indicated that ethical and regulatory guidelines are required, while 7 (1.7%) responded incorrectly.

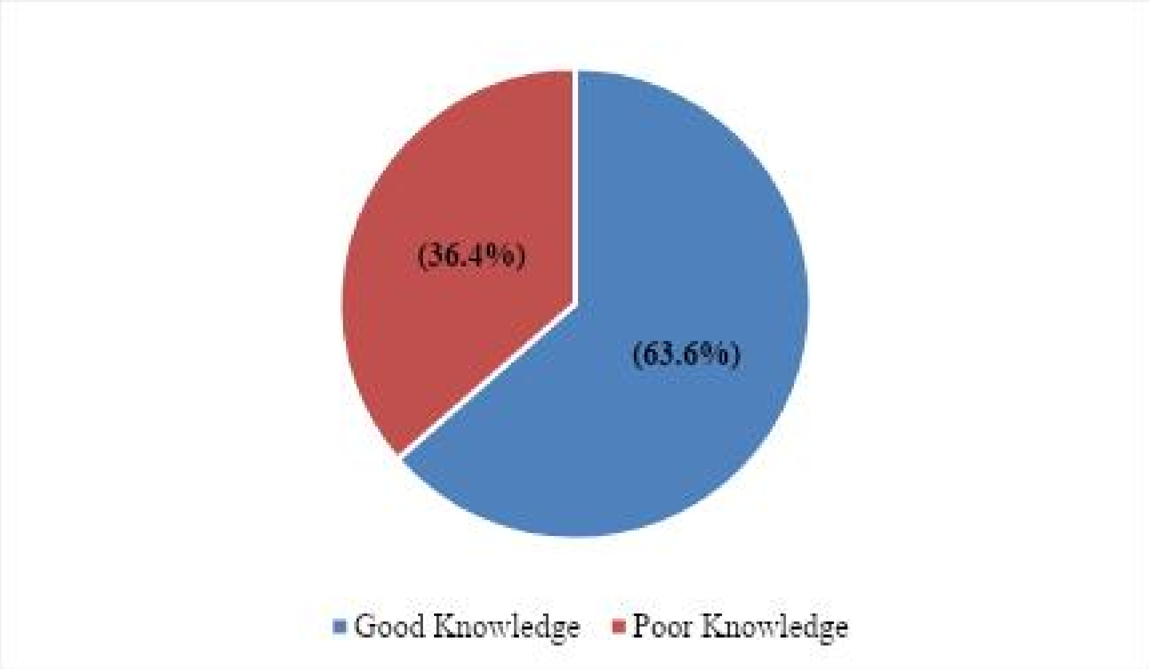

Figure 1: Level of knowledge of artificial intelligence in clinical assessment among healthcare professionals in UBTH

More than three-fifths 260 (63.6%) of the respondents had good knowledge of AI in clinical assessment, while more than one-third 149 (36.4%) had poor knowledge.

Table 5: Factors associated with knowledge of AI in clinical assessment among healthcare professionals in UBTH

Variables	Knowledge of AI		Test statistic	p-value
	Good (n=260) Freq(%)	Poor (n=149) Freq(%)		
Age (Years)				
20–29	121 (58.7)	85 (41.3)	4.545	0.208
30–39	89 (67.4)	43 (32.6)		
40–49	36 (72.0)	14 (28.0)		
50–60	14 (66.7)	7 (33.3)		
Sex				
Male	103 (68.7)	47 (31.3)	2.657	0.103
Female	157 (60.6)	102 (39.4)		
Religion				
Christianity	257 (64.6)	141 (35.4)	6.431*	**0.021**
Islam	3 (27.3)	8 (72.7)		
Ethnicity				
Edo indigene	174 (66.4)	88 (33.6)	2.543	0.111
Non-Edo indigene	86 (58.5)	61 (41.5)		
Marital Status				
Never married	148 (57.6)	109 (42.4)	10.686	**0.001**
Ever married	112 (73.7)	40 (26.3)		
Occupation				
Doctor	121 (74.2)	42 (25.8)	15.677	**0.003**
Nurse	114 (58.8)	80 (41.2)		
Pharmacist	10 (50.0)	10 (50.0)		
Medical Laboratory Scientist	11 (50.0)	11 (50.0)		
Physiotherapist	4 (40.0)	6 (60.0)		
Department				
Nursing Services	114 (58.8)	80 (41.2)	19.049	**0.002**
Medicine	42 (65.6)	22 (34.4)		
Surgery	79 (79.8)	20 (20.2)		
Laboratory Services	11 (50.0)	11 (50.0)		
Pharmaceutical Services	10 (50.0)	10 (50.0)		
Physiotherapy	4 (40.0)	6 (60.0)		
Staff Rank				
Junior staff	129 (56.6)	99 (43.4)	10.872	**<0.001**
Senior staff	131 (72.4)	50 (27.6)		
Years of Work Experience				
<10 years	213 (61.0)	136 (39.0)	6.618	**0.010**
≥10 years	47 (78.3)	13 (21.7)		
Educational Qualification				
Diploma	17 (51.5)	16 (48.5)	7.212	0.205
Bachelor’s degree	192 (64.2)	107 (35.8)		
Postgraduate diploma	17 (56.7)	13 (43.3)		
Master’s degree	19 (63.3)	11 (36.7)		
Fellowship	7 (87.5)	1 (12.5)		

*Fisher's Exact Test.

The proportion of respondents with good knowledge of AI in clinical assessment was highest among those aged 40–49 years (72.0%), followed by 30–39 years (67.4%), 50–60 years (66.7%), and lowest among 20–29 years (58.7%); however, this association was not statistically significant ($\chi^2 = 4.545$, $p = 0.208$). There was no significant association between sex ($p = 0.103$), ethnicity ($p = 0.111$) and knowledge. However, religion was significantly associated with knowledge (Fisher's Exact Test, $p = 0.021$), with Christians having a higher proportion with good knowledge (64.6%) compared to Muslims (27.3%).

Marital status was also significantly associated ($\chi^2 = 10.686$, $p = 0.001$), with ever married respondents having a higher proportion with good knowledge (73.7%) compared to never married (57.6%). Occupation ($\chi^2 = 15.677$, $p = 0.003$) and department ($\chi^2 = 19.049$, $p = 0.002$) were significant, with doctors (74.2%) and those in Surgery (79.8%) having the highest proportions with good knowledge, while physiotherapists (40.0%) and those in Physiotherapy (40.0%) had the lowest. Staff rank ($\chi^2 = 10.872$, $p < 0.001$) and years of work experience ($\chi^2 = 6.618$, $p = 0.010$) were also significantly associated, with senior staff (72.4%) and those with ≥10 years' experience (78.3%) demonstrating higher good knowledge.

Educational qualification was not significantly associated with knowledge ($p = 0.205$).

Table 6: Predictors of good knowledge of AI in clinical assessment among healthcare professionals in UBTH

Predictors	β	Odds ratio	95% CI for OR Lower	Upper	p-value
Age (years)	-0.049	0.952	0.908	0.998	**0.042**
Sex					
Male*		1			
Female	-0.092	0.912	0.537	1.549	0.734
Religion					
Christianity*		1			
Islam	-1.289	0.276	0.069	1.108	0.069
Ethnicity					
Edo Indigene*		1			
Non-Edo Indigene	-0.396	0.673	0.427	1.061	0.088
Marital status					
Never married*		1			
Ever married	0.334	1.396	0.742	2.627	0.300
Occupation					
Doctor*		1			
Nurse	-0.663	0.515	0.287	0.926	**0.026**
Pharmacist	-0.876	0.417	0.152	1.140	0.088
Medical Laboratory Scientist	-1.054	0.348	0.135	0.897	**0.029**
Physiotherapist	-1.586	0.205	0.051	0.827	**0.026**
Staff rank					

Junior staff*		1			
Senior staff	0.686	1.986	0.991	3.980	0.053
Years of work experience					
<10 years*		1			
≥10 years	0.869	2.384	0.934	6.079	0.069
Educational qualification					
Diploma*		1			
Bachelor's degree	0.346	1.414	0.636	3.145	0.396
Postgraduate diploma	0.177	1.194	0.429	3.325	0.734
Master's degree	0.250	1.285	0.414	3.985	0.665
Fellowship	0.871	2.389	0.216	26.411	0.478
Doctorate (PhD)	1.271	3.565	0.350	36.288	0.283

CI = Confidence interval; **OR** = Odd ratio; *reference category; R^2 = 9.3–12.7%

Age and occupation were statistically significant predictors of good knowledge of AI in clinical assessment among healthcare professionals. For each additional year of age, respondents had lower odds of good knowledge (OR = 0.952, 95% CI = 0.908–0.998, p = 0.042). In terms of occupation, nurses, medical laboratory scientists, and physiotherapists had significantly lower odds of good knowledge compared to doctors (OR = 0.515, 95% CI = 0.287–0.926, p = 0.026; OR = 0.348, 95% CI = 0.135–0.897, p = 0.029; and OR = 0.205, 95% CI = 0.051–0.827, p = 0.026, respectively). All other variables were not statistically significant predictors (p > 0.05).

SECTION C:

ATTITUDE TOWARDS THE USE OF ARTIFICIAL INTELLIGENCE IN CLINICAL ASSESSMENT

Table 7: Attitudinal responses towards the use of AI in clinical assessment among healthcare professionals in UBTH

	Attitudinal Responses				
Variables	**SA (n=409) Freq (%)**	**A (n=409) Freq (%)**	**N(n=409) Freq (%)**	**D (n=409) Freq (%)**	**SD (n=409) Freq (%)**
Artificial intelligence can improve the quality of patient care.	113 (27.6)	225 (55.0)	42 (10.3)	11 (2.7)	18 (4.4)
The use of AI in clinical assessments can enhance efficiency in my daily work.	115 (28.1)	233 (57.0)	34 (8.3)	13 (3.2)	14 (3.4)
I feel confident using AI-based tools to support my clinical assessment	76 (18.6)	209 (51.1)	76 (18.6)	22 (5.4)	26 (6.4)
I trust the recommendations provided by AI-based clinical support systems.	38 (9.3)	192 (46.9)	128 (31.3)	32 (7.8)	19 (4.6)
AI should be routinely integrated into clinical practice in tertiary hospitals.	65 (15.9)	178 (43.5)	102 (24.9)	43 (10.5)	21 (5.1)
I am concerned that AI use may negatively affect patient safety.	32 (7.8)	108 (26.4)	112 (27.4)	112 (27.4)	45 (11.0)
AI use in clinical assessment threatens professional autonomy.	41 (10.0)	92 (22.5)	116 (28.4)	107 (26.2)	53 (13.0)
Adequate training would increase my willingness to use AI in clinical practice.	68 (16.6)	162 (39.6)	94 (23.0)	63 (15.4)	22 (5.4)
AI should support, the clinical judgement of healthcare professionals.	67 (16.4)	163 (39.9)	69 (16.9)	77 (18.8)	33 (8.1)
AI should replace the clinical judgement of healthcare professionals.	16 (3.9)	23 (5.6)	22 (5.4)	49 (12.0)	299 (73.1)

***SA=Strongly Agree, A = Agree, N = Neutral, D = Disagree, SD = Strongly Disagree; α= 0.735**

A majority of respondents had a positive attitude towards the use of AI in clinical assessment. Most agreed that AI can improve the quality of patient care, 338 (82.6%), and enhance efficiency in daily work, 348 (85.1%). Over two-thirds expressed confidence in using AI-based tools, 285 (69.7%), although trust in AI recommendations was lower, with 230 (56.2%) agreeing and a substantial proportion remaining neutral, 128 (31.3%).

More than half of respondents supported routine integration of AI into clinical practice in tertiary hospitals, 243 (59.4%), while a notable proportion were neutral, 102 (24.9%). Concerns about AI were mixed; about one-third expressed concern that AI may negatively affect patient safety, 140 (34.2%), while a similar proportion disagreed, 157 (38.4%). Likewise, views on threats to professional autonomy were divided, with 133 (32.5%) agreeing and 160 (39.2%) disagreeing.

Most respondents agreed that adequate training would increase their willingness to use AI, 230 (56.2%), and that AI should support clinical judgement, 230 (56.3%). However, a strong majority rejected the idea that AI should replace clinical judgement, with 348 (85.1%) disagreeing or strongly disagreeing.

Table 8: Appropriateness of attitudinal responses towards AI use in clinical assessment among healthcare professionals in UBTH

	Attitudinal Responses	
Variables	**Appropriate Freq(%)**	**Inappropriate Freq(%)**
Artificial intelligence can improve the quality of patient care.	338 (82.6)	71 (17.4)
The use of AI in clinical assessments can enhance efficiency in my daily work.	348 (85.1)	61 (14.9)
I feel confident using AI-based tools to support my clinical assessment	285 (69.7)	124 (30.3)
I trust the recommendations provided by AI-based clinical support systems.	230 (56.2)	179 (43.8)
AI should be routinely integrated into clinical practice in tertiary hospitals.	243 (59.4)	166 (40.6)
I am concerned that AI use may negatively affect patient safety.	157 (38.4)	252 (61.6)
AI use in clinical assessment threatens professional autonomy.	160 (39.1)	249 (60.9)
Adequate training would increase my willingness to use AI in clinical practice.	230 (56.2)	179 (43.8)
AI should support, the clinical judgement of healthcare professionals.	230 (56.2)	179 (43.8)
AI should replace the clinical judgement of healthcare professionals.	348 (85.1)	61 (14.9)

α= 0.735

A large majority appropriately agreed that AI can improve patient care, 338 (82.6%), and enhance efficiency in clinical work, 348 (85.1%). Similarly, most respondents appropriately rejected the idea that AI should replace clinical judgement, 348 (85.1%). More than half of respondents showed appropriate responses regarding confidence in using AI tools, 285 (69.7%), trust in AI recommendations, 230 (56.2%), routine integration into clinical practice, 243 (59.4%), and the role of AI in supporting clinical judgement, 230 (56.2%).

However, lower proportions of appropriate responses were observed regarding concerns about patient safety, 157 (38.4%), and perceived threats to professional autonomy, 160 (39.1%), indicating areas of uncertainty or concern among respondents.

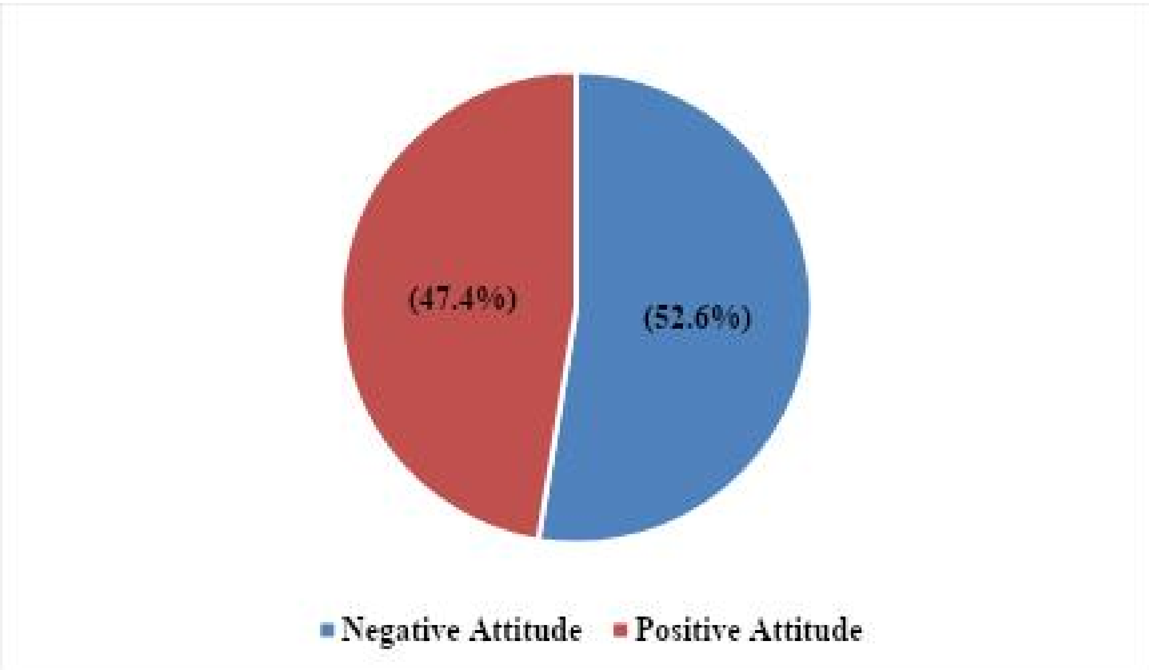

Figure 2: Attitude towards AI use in Clinical assessment among healthcare professionals in UBTH

About half, 215 (52.6%) of the respondents had a negative attitude towards AI use in clinical assessment, while slightly less than half, 194 (47.4%), had a positive attitude.

Table 9: Factors associated with attitude towards AI in clinical assessment among healthcare professionals in UBTH

Variables	Attitude toward AI use		Test statistic	p-value
	Positive (n=194) Freq(%)	Negative (n=215) Freq(%)		
Age (years)				
20–29	97 (47.1)	109 (52.9)	1.566	0.667
30–39	67 (50.8)	65 (49.2)		
40–49	22 (44.0)	28 (56.0)		
50–60	8 (38.1)	13 (61.9)		
Sex				
Male	71 (47.3)	79 (52.7)	0.001	0.976
Female	123 (47.5)	136 (52.5)		
Religion				
Christianity	187 (47.0)	211 (53.0)	1.190	0.275
Islam	7 (63.6)	4 (36.4)		
Ethnicity				
Edo Indigene	113 (43.1)	149 (56.9)	5.413	**0.020**
Non-Edo Indigene	81 (55.1)	66 (44.9)		
Marital status				
Never married	132 (51.4)	125 (48.6)	4.282	**0.039**
Ever married	62 (40.8)	90 (59.2)		
Occupation				
Doctor	90 (55.2)	73 (44.8)	10.096	**0.039**
Nurse	77 (39.7)	117 (60.3)		
Pharmacist	10 (50.0)	10 (50.0)		
Medical Laboratory Scientist	13 (59.1)	9 (40.9)		
Physiotherapist	4 (40.0)	6 (60.0)		
Department				
Nursing Services	77 (39.7)	117 (60.3)	21.826	**0.001**
Medicine	46 (71.9)	18 (28.1)		
Surgery	44 (44.4)	55 (55.6)		
Laboratory Services	13 (59.1)	9 (40.9)		
Pharmaceutical Services	10 (50.0)	10 (50.0)		
Physiotherapy	4 (40.0)	6 (60.0)		
Staff rank				

Junior staff	111 (48.7)	117 (51.3)	0.324	0.569
Senior staff	83 (45.9)	98 (54.1)		
Years of work experience				
<10 years	169 (48.4)	180 (51.6)	0.938	0.333
≥10 years	25 (41.7)	35 (58.3)		
Educational qualification				
Diploma	13 (39.4)	20 (60.6)	8.175*	0.147
Bachelor's degree	138 (46.2)	161 (53.8)		
Postgraduate diploma	13 (43.3)	17 (56.7)		
Master's degree	20 (66.7)	10 (33.3)		
Fellowship	6 (75.0)	2 (25.0)		
Doctorate (PhD)	4 (44.4)	5 (55.6)		
Knowledge level				
Poor knowledge	62 (41.6)	87 (58.4)	3.186	0.074
Good knowledge	132 (50.8)	128 (49.2)		

*Fisher's Exact Test.

With respect to ethnicity, non-Edo indigenes had a higher proportion with positive attitude, 81 (55.1%), compared to Edo indigenes, 113 (43.1%). This association was statistically significant ($\chi^2 = 5.413$, $p = 0.020$). Regarding marital status, respondents who were never married had a higher proportion with positive attitude, 132 (51.4%), compared to those ever married, 62 (40.8%). This association was statistically significant ($\chi^2 = 4.282$, $p = 0.039$).

In terms of occupation, medical laboratory scientists had the highest proportion with positive attitude, 13 (59.1%), while nurses had the lowest, 77 (39.7%). This association was statistically significant ($\chi^2 = 10.096$, $p = 0.039$). With respect to department, respondents in Medicine had the highest proportion with positive attitude, 46 (71.9%), while Nursing Services had the lowest, 77 (39.7%). This association was statistically significant ($\chi^2 = 21.826$, $p = 0.001$).

All other variables, including age, sex, religion, staff rank, years of work experience, educational qualification (Fisher's exact test), and knowledge level, were not statistically significantly associated with attitude ($p > 0.05$).

Table 10: Predictors of positive attitude towards AI use in clinical assessment among healthcare professionals in UBTH

Predictors	β	Odds ratio	95% CI for OR Lower	Upper	p-value
Age (years)	0.017	1.017	0.972	1.064	0.463
Sex					
Male*		1			
Female	0.490	1.632	0.977	2.726	0.061
Religion					
Christianity*		1			
Islam	0.985	2.679	0.711	10.087	0.145
Ethnicity					
Edo Indigene*		1			
Non-Edo Indigene	0.337	1.400	0.902	2.175	0.134
Marital status					
Never married*		1			
Ever married	-0.814	0.443	0.239	0.821	**0.010**
Occupation					
Doctor*		1			
Nurse	-0.809	0.445	0.253	0.784	**0.005**
Pharmacist	-0.312	0.732	0.273	1.965	0.536
Medical Laboratory Scientist	0.103	1.109	0.428	2.874	0.832
Physiotherapist	-0.921	0.398	0.099	1.608	0.196
Staff rank					
Junior staff*		1			
Senior staff	0.075	1.078	0.551	2.109	0.827
Years of work experience					0.376
<10 years*		1			
≥10 years	-0.378	0.685	0.297	1.582	0.376
Educational qualification					0.125
Diploma*		1			
Bachelor's degree	-0.023	0.977	0.430	2.219	0.955
Postgraduate diploma	0.194	1.214	0.428	3.442	0.716
Master's degree	1.025	2.788	0.881	8.826	0.081
Fellowship	1.598	4.944	0.711	34.361	0.106
Doctorate (PhD)	0.292	1.339	0.253	7.097	0.732
Knowledge level					0.032
Poor knowledge*		1			
Good knowledge	0.491	1.634	1.042	2.563	**0.032**

CI = Confidence interval; **OR** = Odd ratio; *reference category; R^2 = 9.1–12.1%

Marital status, occupation (nurses), and knowledge level were statistically significant predictors of positive attitude towards AI use in clinical assessment among healthcare professionals in UBTH.

Ever married respondents had significantly lower odds of a positive attitude compared to those never married (OR = 0.443, 95% CI = 0.239–0.821, $p = 0.010$). Nurses also had significantly lower odds of a positive attitude compared to doctors (OR = 0.445, 95% CI = 0.253–0.784, $p = 0.005$). In contrast, respondents with good knowledge had significantly higher odds of a positive attitude compared to those with poor knowledge (OR = 1.634, 95% CI = 1.042–2.563, $p = 0.032$). All other variables were not statistically significant predictors ($p > 0.05$).

SECTION D:

UPTAKE AND LEVEL OF UTILISATION OF ARTIFICIAL INTELLIGENCE IN CLINICAL ASSESSMENT

Table 11: Uptake and Level of utilisation of AI in clinical assessment

Variables	Frequency (n = 409)	Percent
Ever used any AI tool		
Yes	249	60.9
No	160	39.1
AI tools used* (n=249)		
ChatGPT	236	94.8
Claude	21	8.4
ClinicPal	9	3.6
Stratify AI	7	2.8
Ada Health	6	2.4
VisualDx	6	2.4
QureAI	5	2.0
Gemini	5	2.0
Meta AI	3	1.2
Grok	2	0.8
Copilot	2	0.8
Ubenwa AI	1	0.4
AwaDoc	1	0.4
Area of clinical practice AI tools used*(n=249)		
Diagnosis	151	60.6
Treatment planning	141	56.6
Patient monitoring	57	22.9
Clinical documentation	64	25.7
Workflow/administrative support	48	19.3
Frequency of AI use (n=249)		
Rarely	109	43.8
Daily/Almost Daily	78	31.3
Weekly	47	18.9
Monthly	14	5.6
Never	1	0.4
Duration of AI use (n=249)		
< 1 year	185	74.3
≥ 1 year	64	25.7
AI improves patient care (n=249)		
Yes	213	85.5
Not sure	32	12.9
No	4	1.6
Stopped using AI (n=249)		
No	207	83.1
Yes	42	16.9
Reasons for discontinuing AI use* (n=42)		
Lack of training	6	14.3
Technical issues	10	23.8
Poor workflow integration	13	31.0
Accuracy/safety concerns	23	54.8
Lack of institutional support	5	11.9

*= Multiple response question

Overall, more than half of the respondents had ever used AI tools in clinical assessment, 249 (60.9%), while 160 (39.1%) had never used them. Among users, ChatGPT was by far the most commonly used tool, 236 (94.8%), with all other tools used by only a small proportion of respondents. AI tools were most commonly used for diagnosis, 151 (60.6%), and treatment planning, 141 (56.6%), while fewer respondents reported use for clinical documentation, 64 (25.7%), patient monitoring, 57 (22.9%), and workflow or administrative support, 48 (19.3%).

In terms of frequency, AI use was mostly occasional, with 109 (43.8%) reporting rare use, although 78 (31.3%) reported daily or almost daily use. Most respondents had used AI for less than one year, 185 (74.3%). A large majority reported that AI improves patient care, 213 (85.5%), while only a small proportion were unsure, 32 (12.9%), or disagreed, 4 (1.6%).

Most respondents had not stopped using AI, 207 (83.1%), while 42 (16.9%) had discontinued use. Among those who stopped, the most common reason was concerns about accuracy or safety, 23 (54.8%), followed by poor workflow integration, 13 (31.0%), and technical issues, 10 (23.8%).

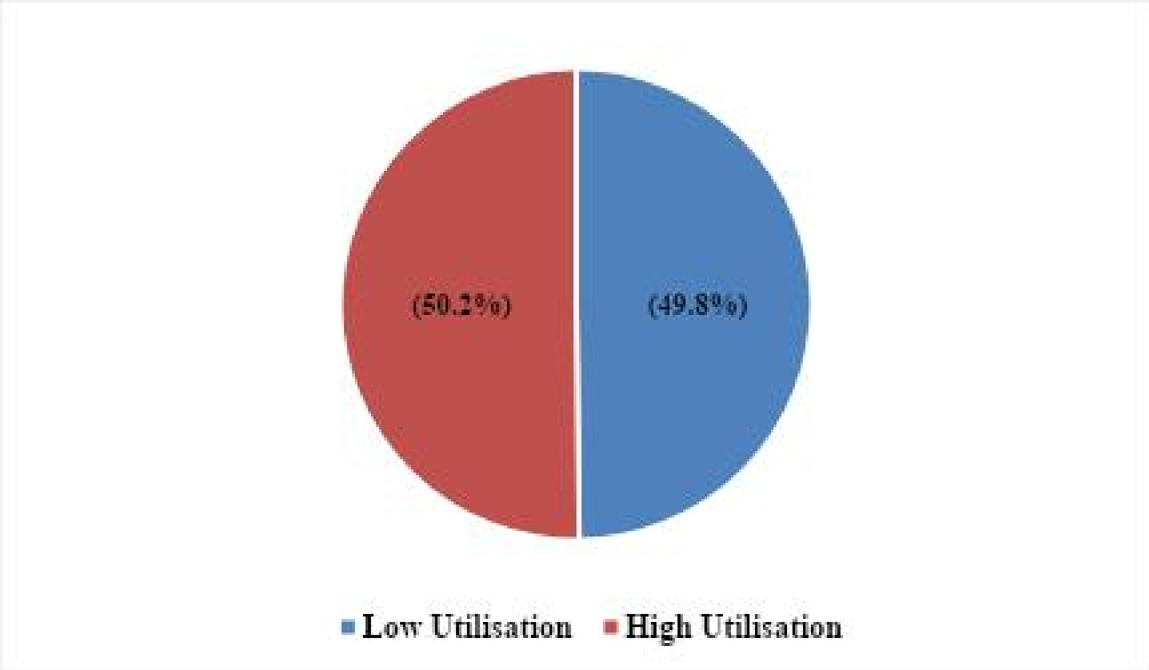

Figure 3: Level of utilisation of AI in clinical assessment among healthcare professionals in UBTH

About half, 125 (50.2%) of the respondents had high utilisation of AI in clinical assessment, while nearly half, 124 (49.8%), had low utilisation.

Table 12: Factors associated with uptake of AI in clinical assessment among healthcare professionals in UBTH

Variables	Uptake		Test statistic	p-value
	Yes (n=249) Freq(%)	**No (n=160) Freq(%)**		
Age (years)				
20–29	133 (64.6)	73 (35.4)	5.958	0.114
30–39	81 (61.4)	51 (38.6)		
40–49	23 (46.0)	27 (54.0)		
50–60	12 (57.1)	9 (42.9)		
Sex				
Male	88 (58.7)	62 (41.3)	0.487	0.485
Female	161 (62.2)	98 (37.8)		
Religion				
Christianity	243 (61.1)	155 (38.9)	0.190*	0.663
Islam	6 (54.5)	5 (45.5)		
Ethnicity				
Edo Indigene	160 (61.1)	102 (38.9)	0.011	0.917
Non-Edo Indigene	89 (60.5)	58 (39.5)		
Marital status				
Never married	168 (65.4)	89 (34.6)	5.852	**0.016**
Ever married	81 (53.3)	71 (46.7)		
Occupation				
Doctor	103 (63.2)	60 (36.8)	2.062	0.724
Nurse	113 (58.2)	81 (41.8)		
Pharmacist	13 (65.0)	7 (35.0)		
Medical Laboratory Scientist	15 (68.2)	7 (31.8)		
Physiotherapist	5 (50.0)	5 (50.0)		
Department				
Nursing Services	113 (58.2)	81 (41.8)	8.233	0.144
Medicine	48 (75.0)	16 (25.0)		
Surgery	55 (55.6)	44 (44.4)		
Laboratory Services	15 (68.2)	7 (31.8)		
Pharmaceutical Services	13 (65.0)	7 (35.0)		
Physiotherapy	5 (50.0)	5 (50.0)		
Staff rank				
Junior staff	149 (65.4)	79 (34.6)	4.324	**0.038**
Senior staff	100 (55.2)	81 (44.8)		
Years of work experience				
<10 years	219 (62.8)	130 (37.2)	3.495	0.062
≥10 years	30 (50.0)	30 (50.0)		
Educational qualification				
Diploma	18 (54.5)	15 (45.5)	6.830	0.234
Bachelor's degree	184 (61.5)	115 (38.5)		
Postgraduate diploma	23 (76.7)	7 (23.3)		
Master's degree	17 (56.7)	13 (43.3)		
Fellowship	3 (37.5)	5 (62.5)		
Doctorate (PhD)	4 (44.4)	5 (55.6)		
Knowledge level				
Poor knowledge	94 (63.1)	55 (36.9)	0.479	0.489
Good knowledge	155 (59.6)	105 (40.4)		
Attitude level				
Negative attitude	119 (55.3)	96 (44.7)	5.823	**0.016**
Positive attitude	130 (67.0)	64 (33.0)		

*Fisher's Exact Test.

The proportion of respondents with high uptake of AI in clinical assessment was highest among those aged 20–29 years (64.6%), followed by 30–39 years (61.4%), 50–60 years (57.1%), and lowest among 40–49 years (46.0%); however, this association was not statistically significant ($\chi^2 = 5.958$, $p = 0.114$). There was no significant association between sex ($p = 0.485$), religion (Fisher's Exact Test, $p = 0.663$), ethnicity ($p = 0.917$), occupation ($\chi^2 = 2.062$, $p = 0.724$), department ($\chi^2 = 8.233$, $p = 0.144$), years of work experience ($\chi^2 = 3.495$, $p = 0.062$), educational qualification ($\chi^2 = 6.830$, $p = 0.234$), or knowledge level ($\chi^2 = 0.479$, $p = 0.489$) and uptake.

However, marital status was significantly associated with uptake ($\chi^2 = 5.852$, $p = 0.016$), with never married respondents having a higher proportion of high uptake (65.4%) compared to ever married (53.3%). Staff rank was also significant ($\chi^2 = 4.324$, $p = 0.038$), with junior staff demonstrating higher uptake (65.4%) compared to senior staff (55.2%). Attitude level showed a significant association ($\chi^2 = 5.823$, $p = 0.016$), with respondents with positive attitude having higher uptake (67.0%) compared to those with negative attitude (55.3%).

Table 13: Factors associated with level of utilisation of AI in clinical assessment among healthcare professionals in UBTH

Variables	Level of Utilisation		Test statistic	p-value
	High (n=125) Freq(%)	Low (n=124) Freq(%)		
Age (years)				
20–29	77 (57.9)	56 (42.1)	13.887	**0.003**
30–39	39 (48.1)	42 (51.9)		
40–49	8 (34.8)	15 (65.2)		
50–60	1 (8.3)	11 (91.7)		
Sex				
Male	40 (45.5)	48 (54.5)	1.226	0.268
Female	85 (52.8)	76 (47.2)		
Religion				
Christianity	121 (49.8)	122 (50.2)	0.667*	0.414
Islam	4 (66.7)	2 (33.3)		
Ethnicity				
Edo Indigene	79 (49.4)	81 (50.6)	0.122	0.727
Non-Edo Indigene	46 (51.7)	43 (48.3)		
Marital status				
Never married	94 (56.0)	74 (44.0)	6.834	**0.009**
Ever married	31 (38.3)	50 (61.7)		
Occupation				
Doctor	48 (46.6)	55 (53.4)	3.028*	0.553
Nurse	58 (51.3)	55 (48.7)		
Pharmacist	6 (46.2)	7 (53.8)		
Medical Laboratory Scientist	9 (60.0)	6 (40.0)		
Physiotherapist	4 (80.0)	1 (20.0)		
Department				
Nursing Services	58 (51.3)	55 (48.7)	5.086*	0.405
Medicine	26 (54.2)	22 (45.8)		
Surgery	22 (40.0)	33 (60.0)		
Laboratory Services	9 (60.0)	6 (40.0)		
Pharmaceutical Services	6 (46.2)	7 (53.8)		
Physiotherapy	4 (80.0)	1 (20.0)		
Staff rank				
Junior staff	86 (57.7)	63 (42.3)	8.386	**0.004**
Senior staff	39 (39.0)	61 (61.0)		
Years of work experience				
<10 years	119 (54.3)	100 (45.7)	12.445	**<0.001**
≥10 years	6 (20.0)	24 (80.0)		
Educational qualification				
Diploma	9 (50.0)	9 (50.0)	2.606*	0.761
Bachelor's degree	90 (48.9)	94 (51.1)		
Postgraduate diploma	15 (65.2)	8 (34.8)		
Master's degree	8 (47.1)	9 (52.9)		
Fellowship	1 (33.3)	2 (66.7)		
Doctorate (PhD)	2 (50.0)	2 (50.0)		
Knowledge level				
Poor knowledge	50 (53.2)	44 (46.8)	0.540	0.462
Good knowledge	75 (48.4)	80 (51.6)		
Attitude level				
Negative attitude	50 (42.0)	69 (58.0)	6.107	**0.013**
Positive attitude	75 (57.7)	55 (42.3)		
Uptake				
Ever used	125(50.2)	124(49.8)	113.321	**<0.001**
Never used	0(0.0)	160(100.0)		

*Fisher's Exact Test.

With respect to age group, the highest proportion of respondents with high level of utilisation was observed among those aged 20–29 years, 77 (57.9%), while the lowest proportion was among those aged 50–60 years, 1 (8.3%). This association was statistically significant (χ^2 = 13.887, p = 0.003). Regarding marital status, respondents who were never married had a higher proportion with high utilisation, 94 (56.0%), compared to those who were ever married, 31 (38.3%). This association was statistically significant (χ^2 = 6.834, p = 0.009).

In terms of staff rank, junior staff had a higher proportion with high utilisation, 86 (57.7%), compared to senior staff, 39 (39.0%). This association was statistically significant (χ^2 = 8.386, p = 0.004). With respect to years of work experience, respondents with less than 10 years' experience had a higher proportion with high utilisation, 119 (54.3%), compared to those with ≥10 years, 6 (20.0%). This association was statistically significant (χ^2 = 12.445, $p < 0.001$).

Finally, respondents with a positive attitude had a higher proportion with high utilisation, 75 (57.7%), compared to those with negative attitude, 50 (42.0%). This association was statistically significant (χ^2 = 6.107, p = 0.013). All other variables, including sex, religion, ethnicity, occupation, department, educational qualification, and knowledge level, were not statistically significantly associated with level of utilisation ($p > 0.05$).

Table 14: Predictors of uptake of AI in clinical assessment among healthcare professionals in UBTH

Predictors	β	Odds ratio	95% CI for OR Lower	Upper	p-value
Age (years)	0.007	1.007	0.963	1.054	0.745
Sex					
Male*		1			
Female	0.268	1.308	0.780	2.193	0.309
Religion					
Christianity*		1			
Islam	-0.375	0.687	0.193	2.440	0.561
Ethnicity					
Edo Indigene*		1			
Non-Edo Indigene	-0.176	0.838	0.536	1.312	0.440
Marital status					
Never married*		1			
Ever married	-0.375	0.687	0.377	1.252	0.220
Occupation					
Doctor*		1			
Nurse	-0.452	0.636	0.359	1.129	0.122
Pharmacist	-0.058	0.944	0.335	2.657	0.913
Medical Laboratory Scientist	0.033	1.033	0.384	2.782	0.949
Physiotherapist	-0.704	0.495	0.124	1.968	0.318
Staff rank					
Junior staff*		1			
Senior staff	-0.177	0.837	0.429	1.636	0.604
Years of work experience					
<10 years*		1			
≥10 years	-0.079	0.924	0.416	2.053	0.847
Educational qualification					
Diploma*		1			
Bachelor's degree	0.342	1.408	0.629	3.149	0.405
Postgraduate diploma	1.153	3.169	1.040	9.651	**0.042**
Master's degree	0.212	1.237	0.406	3.767	0.708
Fellowship	-0.615	0.541	0.093	3.159	0.495
Doctorate (PhD)	-0.077	0.926	0.177	4.855	0.928
Knowledge level					
Poor knowledge*		1			
Good knowledge	-0.151	0.859	0.548	1.349	0.510
Attitude level					
Negative attitude*		1			
Positive attitude	0.464	1.590	1.034	2.447	**0.035**

CI = Confidence interval; **OR** = Odd ratio; *reference category; R^2 = 5.3–7.2%

Educational qualification (postgraduate diploma) and attitude level were statistically significant predictors of uptake of AI in clinical assessment among healthcare professionals in UBTH. Respondents with a postgraduate diploma had significantly higher odds of AI uptake compared to those with a diploma (OR = 3.169, 95% CI = 1.040–9.651, $p = 0.042$). Similarly, those with a positive attitude had significantly higher odds of AI uptake compared to those with a negative attitude (OR = 1.590, 95% CI = 1.034–2.447, $p = 0.035$). All other variables were not statistically significant predictors ($p > 0.05$).

Table 15: Predictors of high level of utilisation of AI in clinical assessment among healthcare professionals in UBTH

Predictors	β	Odds ratio	95% CI for OR Lower	Upper	p-value
Age (years)	-0.027	0.974	0.914	1.037	0.405
Sex					
Male*		1			
Female	0.221	1.247	0.650	2.394	0.506
Religion					
Christianity*		1			
Islam	0.485	1.624	0.246	10.698	0.614
Ethnicity					
Edo Indigene*		1			
Non-Edo Indigene	0.055	1.057	0.588	1.899	0.853
Marital status					
Never married*		1			
Ever married	-0.089	0.915	0.425	1.969	0.819
Occupation					
Doctor*		1			
Nurse	0.094	1.098	0.524	2.304	0.804
Pharmacist	-0.262	0.770	0.217	2.734	0.686
Medical Laboratory Scientist	0.343	1.409	0.439	4.520	0.565
Physiotherapist	1.541	4.667	0.475	45.875	0.186
Staff rank					
Junior staff*		1			
Senior staff	-0.145	0.865	0.387	1.932	0.723
Years of work experience					
<10 years*		1			
≥10 years	-1.044	0.352	0.095	1.306	0.119
Educational qualification					
Diploma*		1			
Bachelor's degree	0.187	1.206	0.403	3.605	0.738
Postgraduate diploma	0.803	2.232	0.589	8.454	0.237
Master's degree	0.224	1.251	0.264	5.938	0.778
Fellowship	0.273	1.314	0.076	22.862	0.851
Doctorate (PhD)	1.549	4.707	0.360	61.521	0.238
Knowledge level					
Poor knowledge*		1			
Good knowledge	-0.080	0.923	0.518	1.644	0.785
Attitude level					
Negative attitude*		1			
Positive attitude	0.631	1.879	1.069	3.304	**0.028**

CI = Confidence interval; **OR** = Odd ratio; *reference category; R^2 = 10.9–14.6%

Only attitude level was a statistically significant predictor of high level of utilisation of AI in clinical assessment among healthcare professionals in UBTH. Respondents with a positive attitude had significantly higher odds of high utilisation compared to those with a negative attitude (OR = 1.879, 95% CI = 1.069–3.304, $p = 0.028$). All other variables, including age, sex, religion, ethnicity, marital status, occupation, staff rank, years of work experience, educational qualification, and knowledge level, were not statistically significant predictors ($p > 0.05$).

SECTION E:

FACTORS INFLUENCING THE USE AI IN CLINICAL ASSESSMENT

Table 16: Factors influencing the use of AI in clinical assessment among healthcare professionals in UBTH

Variables	Frequency (n = 409)	Percent
Unclear ethical guidelines limit AI use		
Yes	369	90.2
No	40	9.8
AI enhances efficiency		
Yes	380	92.9
No	29	7.1
AI is easy to learn		
Yes	360	88.0
No	49	12.0
AI integrates smoothly into workflow		
Yes	353	86.3
No	56	13.7
Patient attitude influences AI use		
Yes	241	58.9
No	168	41.1
Colleague use influences AI adoption		
Yes	297	72.6
No	112	27.4
Infrastructure available for AI use		
Yes	232	56.7
No	177	43.3
Workload limits AI use		
Yes	230	56.2
No	179	43.8
Institutional training available		
No	209	51.1
Yes	200	48.9
Data privacy concerns limit AI use		
Yes	278	68.0
No	131	32.0
Cost/funding limits AI use		
Yes	311	76.0
No	98	24.0

A large majority of respondents reported that unclear ethical guidelines limit AI use, 369 (90.2%), and that AI enhances efficiency, 380 (92.9%). Most respondents also indicated that AI is easy to learn, 360 (88.0%), and integrates smoothly into workflow, 353 (86.3%).

More than half of respondents reported that patient attitude influences AI use, 241 (58.9%), while 297 (72.6%) indicated that colleague use influences AI adoption.

Slightly over half reported that infrastructure is available for AI use, 232 (56.7%), and that workload limits AI use, 230 (56.2%). However, institutional training was lacking, as 209 (51.1%) reported that training was not available. A substantial proportion of respondents reported data privacy concerns, 278 (68.0%), and cost or funding limitations, 311 (76.0%), as barriers to AI use.

Table 17: Association between level of utilisation and factors influencing AI use in clinical assessment among healthcare professionals in UBTH

Variables	Level of utilisation of AI		Test Statistic	p-Value
	High(n=125) Frequency(%)	Low(n=124) Frequency(%)		
Unclear ethical guidelines limit use				
No	16 (57.1)	12 (42.9)	0.608	0.435
Yes	109 (49.3)	112 (50.7)		
AI enhances efficiency				
No	10 (52.6)	9 (47.4)	0.049	0.825
Yes	115 (50.0)	115 (50.0)		
AI is easy to learn				
No	11 (36.7)	19 (63.3)	2.499	0.114
Yes	114 (52.1)	105 (47.9)		
AI integrates smoothly into workflow				
No	13 (39.4)	20 (60.6)	1.777	0.182
Yes	112 (51.9)	104 (48.1)		
Patient attitude influences use				
No	67 (56.8)	51 (43.2)	3.883	**0.049**
Yes	58 (44.3)	73 (55.7)		
Colleague use influences adoption				
No	36 (55.4)	29 (44.6)	0.945	0.331
Yes	89 (48.4)	95 (51.6)		
Infrastructure available				
No	49 (46.2)	57 (53.8)	1.166	0.280
Yes	76 (53.1)	67 (46.9)		
Workload limits use				
No	52 (47.3)	58 (52.7)	0.676	0.411
Yes	73 (52.5)	66 (47.5)		
Institutional training available				
No	67 (50.4)	66 (49.6)	0.004	0.953
Yes	58 (50.0)	58 (50.0)		
Data privacy concerns				
No	49 (56.3)	38 (43.7)	2.004	0.157
Yes	76 (46.9)	86 (53.1)		

With respect to patient attitude, respondents who reported that patient attitude did not influence AI use had a higher proportion with high level of utilisation, 67 (56.8%), compared to those who reported that patient attitude influenced use, 58 (44.3%). This association was statistically significant ($\chi^2 = 3.883$, $p = 0.049$). All other factors, including unclear ethical guidelines, perceived efficiency of AI, ease of learning, integration into workflow, colleague influence, availability of infrastructure, workload, institutional training, and data privacy concerns, were not statistically significantly associated with level of utilisation ($p > 0.05$).

TABLE 18: Predictors of High level of utilization among factors influencing AI use among healthcare professionals in UBTH

Predictors	β	Odds ratio	95% CI for OR Lower	Upper	p-value
Unclear ethical guidelines limit use					
No*		1			
Yes	-0.087	0.917	0.386	2.179	0.844
AI enhances efficiency					
No*		1			
Yes	-0.468	0.626	0.221	1.774	0.378
AI is easy to learn					
No*		1			
Yes	0.635	1.888	0.729	4.890	0.191
AI integrates smoothly into workflow					
No*		1			
Yes	0.382	1.465	0.607	3.535	0.396
Patient attitude influences use					
No*		1			
Yes	-0.374	0.688	0.389	1.216	0.198
Colleague use influences adoption					
No*		1			
Yes	-0.111	0.895	0.474	1.689	0.732
Infrastructure available					
No*		1			
Yes	0.328	1.388	0.799	2.409	0.245
Workload limits use					
No*		1			
Yes	0.455	1.577	0.902	2.756	0.110
Institutional training available					
No*		1			
Yes	-0.201	0.818	0.466	1.436	0.484
Data privacy concerns					
No*		1			
Yes	-0.382	0.683	0.381	1.223	0.199
Cost/funding limits AI use					
No*		1			
Yes	0.166	1.180	0.621	2.243	0.612

CI = Confidence interval; **OR** = Odd ratio; *reference category; R^2 = 4.9–6.6%

None of the assessed factors, including unclear ethical guidelines, perceived efficiency of AI, ease of learning, integration into workflow, patient attitude, colleague influence, availability of infrastructure, workload, institutional training, and data privacy concerns, were significant predictors of AI utilisation ($p > 0.05$).

CHAPTER FIVE

5.1 DISCUSSION

The respondents of this study were mostly young adults with a mean age in the early thirties. This may be because older healthcare professionals are more likely to occupy senior staff positions with reduced clinical workload, making them less available for routine hospital-based activities. More than half of respondents were female. This may reflect the gender distribution within the healthcare workforce in the study setting, particularly the predominance of females in nursing and certain allied health professions. It may also be influenced by greater availability and willingness of female healthcare workers to participate during the data collection period. Almost all were Christians, which is likely due to the study being carried out in the south-south of Nigeria, a predominantly Christian area. Similarly, Edo indigenes made up a larger proportion of the study population, which is expected given that the study was carried out in Edo State. More than half of the respondents had never married, which may be explained by the relatively young age structure of the hospital workforce, which is largely composed of early-career professionals. In terms of occupational distribution, Nurses and doctors made up the largest proportion of respondents, with most participants being in the junior cadre. In addition, the majority held a bachelor's degree, while fellowship and doctorate holders were few. This profile is typical of a large Nigerian teaching hospital, where the bulk of day-to-day clinical work is carried out by younger nurses and doctors, with fewer staff at the senior and highly specialised levels.

A similar pattern was reported by a descriptive cross-sectional study conducted among 384 staff of the Federal Medical Centre, Makurdi, Benue State, Nigeria, which found a workforce of relatively young healthcare professionals with tertiary qualifications and varying exposure to artificial intelligence.[35] Similarly, a cross-sectional study among 441 healthcare professionals in Mogadishu, Somalia, also found that the study population was largely made up of working-age health workers with formal clinical training and a youthful workforce structure.[33] This finding has implications for workforce planning, as it suggests that UBTH has a population of staff who can be trained in digital health innovation; however, any such effort will only succeed if the training, workflow support, and governance arrangements are designed with the needs of these specific cadres in mind. Hospital administrators should therefore develop AI capacity-building programmes that cut across disciplines, are accessible to early-career staff, and account for differences in professional background and rank.

This study found that all respondents were aware of AI, with the major sources of information being the internet and social media. More than three-fifths of the respondents had good knowledge of artificial intelligence in clinical assessment, while more than one-third had poor knowledge. Respondents performed well in recognising the basic definition of AI, its role in supporting clinical decision-making, its benefits for accuracy and efficiency, the risk of algorithmic bias, and the requirement for ethical and regulatory safeguards. Familiarity was highest for ChatGPT, while awareness of other AI tools with clinical applications was considerably lower. This pattern is not difficult to explain. The relatively good overall knowledge is consistent with the academic and professional background of healthcare workers in a tertiary institution, where exposure to clinical innovation tends to be higher than in lower-level facilities. The prominent role of the internet and social media as sources of information also suggests that much of the AI knowledge held by respondents was acquired through informal digital channels rather than structured institutional training. That said, the low recognition of specific clinical AI tools suggests that respondents may possess a general awareness of artificial intelligence, but have limited knowledge of its specialised clinical applications, with familiarity being greater for consumer-oriented platforms than for professional healthcare tools. This is not unexpected, given that AI in Nigerian healthcare is still an emerging area, and formal curriculum integration and tool-specific training are still limited in most hospitals. A cross-sectional study among 1,007 physicians in Sudan similarly found high awareness of AI in medicine but limited formal training in the subject.[34] A descriptive cross-sectional study conducted at the Federal Medical Centre, Makurdi, Nigeria, also reported that while awareness of AI was present, only a small proportion had in-depth knowledge of its clinical applications.[35] Superficial knowledge is a concern because it can create confidence without genuine competence, thereby increasing the risk of inappropriate AI use, poor judgement about when to trust AI output, or failure to spot when a tool is producing unreliable results. Hospital management should therefore go beyond awareness campaigns and put in place formal, clinically oriented, and tool-specific training on artificial intelligence for healthcare professionals.

Religion, marital status, occupation, department, staff rank, and years of work experience were all significantly associated with knowledge of artificial intelligence in clinical assessment. Ever-married respondents, doctors, those in surgery, senior staff, and those with longer work experience tended to have stronger knowledge, while respondents in physiotherapy showed the weakest pattern. These differences are most likely linked to variations in clinical exposure, institutional responsibility, and the degree to which different cadres engage with technologies that support clinical reasoning. Doctors and surgical staff routinely work in contexts that involve diagnostic support, image interpretation, and high-stakes clinical decisions, and are more likely to have encountered discussions about AI in those contexts. Senior staff and those with longer experience may also have accumulated exposure through workshops, conferences, and hospital policy discussions. A descriptive cross-sectional study conducted among medical practitioners in two tertiary institutions in Port Harcourt, South-South Nigeria, reported that awareness and understanding of AI varied with professional role and level of exposure.[36] A cross-sectional study in Mogadishu, Somalia, similarly found that cadre and experience influenced the spread of AI knowledge among healthcare workers.[33] This uneven distribution of knowledge across professions and departments is a concern because it may translate into uneven readiness for AI adoption and could widen disparities in the safe use of digital clinical tools within the same institution. Hospital educators should therefore direct targeted AI training especially towards non-physician groups and departments with lower baseline exposure.

On multivariate analysis, age and occupation remained the statistically significant predictors of good knowledge of artificial intelligence in clinical assessment. For each additional year of age, respondents had lower odds of having good knowledge, indicating that the likelihood of good AI knowledge declined gradually with increasing age in this workforce. Younger professionals are likely to have had more recent exposure to digital tools during their training and may be more comfortable using internet-based channels where AI is frequently discussed. Nurses, medical laboratory scientists, and physiotherapists all had significantly lower odds of good knowledge compared with doctors. The occupational difference probably reflects the fact that doctors are more centrally involved in diagnostic reasoning, treatment planning, and clinical documentation, all of which are areas where AI is commonly presented as a decision-support tool. A cross-sectional survey among German surgeons found that clinicians' familiarity with AI varied with experience and specialty-specific exposure.[32] A cross-sectional study among Sudanese physicians likewise reported that differences in education and training exposure shaped knowledge of AI in medicine.[34] These age-related and profession-related knowledge gaps are a concern because they may result in inequitable implementation and create pockets of underprepared users within the hospital. Hospital management and university administrators should therefore provide profession-sensitive AI training that deliberately includes older staff and non-physician cadres.

This study found that slightly more than half of the respondents had a negative attitude towards the use of artificial intelligence in clinical assessment, while slightly less than half had a positive attitude. Despite this, many respondents, when responding to specific attitudinal items, agreed that AI could improve patient care and enhance efficiency, and a large proportion rejected the idea that AI should replace clinical judgement. Trust in AI recommendations, concerns about patient safety, and views on professional autonomy were less settled and showed more division. The respondents seem to appreciate the practical value AI could offer, particularly in terms of support and efficiency, but remain hesitant about its trustworthiness, legal standing, and implications for professional practice. This is understandable in a Nigerian context where AI is still more of a future possibility than a fully governed and institutionally embedded tool. Clinicians may grasp the potential benefit at a general level while still being concerned about errors, bias, data privacy, and medico-legal risks. The broad acceptance of AI as a supportive rather than a replacement tool also suggests that the resistance observed here is not so much a rejection of technology as it is a concern about the boundaries of human judgement and professional responsibility. A cross-sectional survey among German surgeons found comparable patterns, with respondents acknowledging AI's potential while remaining concerned about legal liability, reliability, and ethical issues.[32] A cross-sectional study conducted in 2023 across six geopolitical zones in Nigeria also found that many healthcare professionals believed AI could improve efficiency but maintained substantial concerns about ethical challenges and the wider consequences of adoption.[28] Negative or ambivalent attitudes can slow institutional uptake even where knowledge is reasonably good and digital tools are already available. Hospital leaders should therefore address clinicians' specific concerns directly through training, ethical guidance, and transparent governance, rather than assuming that enthusiasm for AI will drive adoption on its own.

Ethnicity, marital status, occupation, and department were all significantly associated with attitude towards artificial intelligence in clinical assessment. Non-Edo indigenes, never-married respondents, medical laboratory scientists, and those in the Medicine department showed stronger positive attitude patterns, while nurses and respondents in Nursing Services showed weaker positive patterns. These associations are likely rooted in differences in role expectations, workload, and how useful AI appears to be in different practice settings. Respondents in medicine and laboratory-facing roles may be more inclined to see AI as a useful tool for analytical work, whereas nurses, who typically manage high patient loads and are responsible for complex bedside care, may view AI as an additional demand unless it is clearly embedded into their workflow. The marital-status pattern may reflect differences in available time, competing obligations, and openness to experimenting with new technologies. A cross-sectional study conducted in 2023 among 263 healthcare professionals in Nigeria found that while respondents generally acknowledged AI's potential, fear of replacement and concerns about professional consequences still shaped their perceptions.[9] A cross-sectional study spanning six geopolitical zones in Nigeria reported mixed attitudes driven by both perceived usefulness and ethical concerns.[28] Since attitudinal resistance can cluster around specific subgroups within a hospital, it may limit institution-wide adoption if it is not deliberately addressed. Hospital management should design profession-specific trust-building and attitude-change strategies, especially targeting groups whose day-to-day work makes them more likely to be cautious about AI.

On multivariate analysis, marital status, occupation, and knowledge level were the statistically significant predictors of positive attitude towards artificial intelligence in clinical assessment. Ever-married respondents had significantly lower odds of a positive attitude compared with those who had never married, nurses had significantly lower odds compared with doctors, and respondents with good knowledge had significantly higher odds of a positive attitude compared with those with poor knowledge. In practical terms, better understanding of AI was associated with greater acceptance, while the social and professional realities of being married and working as a nurse reduced the odds of a positive attitude. Knowledge probably improves acceptance by reducing uncertainty and strengthening the sense that AI is useful and manageable, whereas the combined demands of heavy workload, additional domestic responsibilities, and the practical nature of nursing work may heighten caution towards tools that have not yet been smoothly incorporated into daily practice. A cross-sectional study conducted among 263 healthcare professionals in Nigeria found that knowledge and perception were closely linked in determining how healthcare workers viewed AI adoption.[9] Another study among physicians and nurses similarly found that perceived usefulness and attitudes about risk strongly shaped intention to use medical AI.[52] Since better knowledge appears to be a pathway to improved acceptance, health educators should combine AI literacy programmes with trust-building measures and workflow-sensitive orientation, with particular attention to nurses and other groups that have shown lower attitudinal readiness.

This study found that more than half of the respondents had ever used an artificial intelligence tool in clinical assessment. Among users, ChatGPT was by far the most commonly used tool, diagnosis and treatment planning were the main areas of application, and use was more often occasional than routine. Most users had been using AI for less than one year, most believed it improved patient care, and nearly all expressed willingness to continue using AI. The most frequently cited reasons for discontinuing use were concerns about accuracy or safety and poor workflow integration. This pattern suggests that uptake has been driven largely by the accessibility and general familiarity of ChatGPT rather than by any deliberate institutional deployment of specialised clinical systems. ChatGPT is freely available and easy to try out informally for information support, explanation, and drafting tasks, without requiring any hospital-level procurement or approval. More specialised clinical AI tools, by contrast, require specific awareness, local infrastructure, workflow integration, and training that are not yet in place in this setting. The fact that initial uptake has occurred without translating into routine use suggests that many respondents are willing to experiment with AI but have not yet moved to sustained, integrated clinical use. A 2024 cross-sectional study conducted among 227 healthcare professionals at the University of Uyo Teaching Hospital, Nigeria, similarly found relatively high initial uptake of AI but limited routine departmental use.[29] A 2024 narrative review of ChatGPT use in medicine also reported that while clinicians are increasingly exploring the tool for clinical support and documentation tasks, routine integration in real clinical settings remains largely experimental.[38] Early uptake without adequate governance and workflow integration is a concern because it may produce scattered, informal use rather than safe and systematic benefit. Hospital management should therefore move beyond tolerating informal AI use and establish clear institutional pathways that specify when, how, and for what purposes AI tools should be used in clinical practice.

On multivariate analysis, educational qualification and attitude were the statistically significant predictors of uptake of AI in clinical assessment. Respondents with a postgraduate diploma had significantly higher odds of AI uptake than those with a diploma and respondents with a positive attitude had significantly higher odds of uptake than those with a negative attitude. This indicates that actual experimentation with AI is more likely among healthcare professionals who have advanced further educationally and among those who are already favourably disposed towards AI. Postgraduate training likely exposes respondents to research, evidence appraisal, and more independent digital tool use, which in turn builds both the confidence and the opportunity to explore AI. Attitude, on the other hand, functions as a bridge between knowledge and behaviour: professionals who find AI useful and acceptable are more likely to move from awareness to actual use. A 2022 scoping review across 45 studies of AI implementation in healthcare found that real-world adoption tends to be concentrated among users and in settings where AI can feasibly be incorporated into professional routines.[39] A 2023 scoping review of AI in essential health services across WHO regions reported that uptake remains uneven and is heavily constrained in lower-resource settings by skill and implementation barriers.[40] These findings highlight the importance of improving AI literacy and fostering positive attitudes towards AI among healthcare professionals, as these may enhance uptake and support more efficient, evidence-based clinical assessment and healthcare delivery. University administrators should therefore build AI exposure into postgraduate and continuing professional education while also working to address the negative perceptions that hold back first-time use.

Among those who had used artificial intelligence, high level of utilisation was less common than low level of utilisation. The significant predictors of higher utilisation included younger age, never-married status, junior cadre, shorter work experience, and a positive attitude. Sustained and more frequent use of AI requires not only access but also confidence, flexibility, and an environment that supports its incorporation into daily work. Younger and junior staff are likely to be more digitally adaptable, less anchored to established clinical routines, and more willing to try out new approaches. More experienced and senior staff may be more cautious, whether because of deeply ingrained clinical habits, greater awareness of medico-legal risk, or a stronger sense of responsibility for final clinical decisions. Likewise, the burden of additional domestic responsibilities may limit the time and attention available for AI use, as observed with the ever married population. Respondents with a positive attitude are also more likely to incorporate the use of AI into their regular workflow given their attitudinal disposition. A review of AI use in healthcare across Africa similarly found that implementation remains low, with resource, training, and confidence barriers continuing to restrict routine use.[42] A scoping review of AI implementation in healthcare practice also found that many tools are discussed and piloted but relatively few become embedded in day-to-day care.[39] Low routine utilisation is a concern because it means the potential benefits of AI for efficiency and decision support may go unrealised even among staff who have already started using it. Hospital leadership should therefore focus on supporting the transition from occasional experimentation to safe routine use, through workflow redesign, adequate supervision, and clear implementation guidance.

Only attitude level remained a statistically significant predictor of high level of utilisation after controlling for other variables. Respondents with a positive attitude had significantly higher odds of high utilisation compared with those with a negative attitude. This means that once a respondent had started using AI at all, the depth and frequency of their use depended more on how they felt about AI than on their demographic or professional characteristics. Sustained utilisation requires trust, comfort, and a willingness to rely repeatedly on a tool under real clinical conditions. A clinician may have a reasonable understanding of what AI is and may even have used it on one or two occasions, but if underlying concerns about safety, professional autonomy, or reliability persist, continued and frequent use is unlikely. A 2025 study among physicians and nurses found that attitudes and perceptions strongly shaped intention to use medical AI.[52] A 2025 systematic review on trust in AI-based clinical decision support systems also identified trust as a central mediator of use in healthcare settings.[51] These findings indicate that hospital investments in training and digital infrastructure will have a limited effect if clinicians do not sufficiently trust AI to use it on a regular basis. Policy makers and health educators should therefore prioritise trust-building strategies, including transparent operational guidelines, supervised use cases, and clearly defined boundaries for human oversight in AI-supported care.

Finally, the factors perceived to influence AI use in this study were predominantly ethical, organisational, and infrastructural in nature. Nearly all respondents believed that AI enhances efficiency, is easy to learn, and could be integrated into clinical workflows, yet an equally large proportion indicated that unclear ethical guidelines were a barrier to its use. More than half reported that patient attitudes, infrastructure, and workload influenced their use of AI, about half said that institutional training was not available, and substantial proportions identified data privacy concerns and cost or funding limitations as barriers. Respondents appear to view AI as promising in theory but inadequately supported in practice. This is consistent with the broader Nigerian health-system context, where digital innovations often advance more quickly than the local governance, funding mechanisms, and institutional structures needed to support them safely. In such a context, clinicians may be willing to use AI but remain constrained by uncertainties about what is permissible, what is safe, who bears responsibility for AI-supported decisions, whether the tools fit into routine care, and whether the required infrastructure will be reliably available. A 2022 qualitative interview study conducted in Germany among specialists working in human-AI collaboration found that trust, workflow compatibility, transparency, and human agency were key determinants of adoption.[43] A 2024 scoping review by researchers at the University of Victoria, Canada, similarly identified trust, governance, legal frameworks, data security, and workflow integration as the main barriers and facilitators of AI adoption in healthcare.[44] These findings confirm that AI adoption in UBTH is not simply a technical challenge but a systems-level issue that involves governance, infrastructure, cost, and user trust. The hospital management and relevant health authorities should establish clear ethical and operational guidelines, invest in institutional training, address infrastructure gaps, and put in place governance frameworks that make AI adoption safe, legally sound, and genuinely useful in clinical practice.

Among the assessed influencing factors, patient attitude was the only significant predictor of high level of utilisation. Respondents who said that patient attitude did not influence their AI use showed a higher proportion of high utilisation compared with those who felt patient attitude did influence their use. Clinicians who are concerned about how patients perceive AI may be more cautious about using it frequently, particularly in a context where many patients may not fully understand AI-supported decision-making and where clinicians may fear that such tools could undermine patient confidence or be misunderstood. In contrast, those who do not feel constrained by patient perception may be more willing to use AI as an internal decision-support tool. A 2024 scoping review of AI adoption in healthcare noted that trust and social acceptance were important barriers to utilisation.[44] A commentary on AI adoption in sub-Saharan Africa similarly identified contextual acceptance, infrastructure, and broader social conditions as critical determinants of meaningful implementation.[45] This finding suggests that clinician behaviour around AI may be shaped not only by their own professional readiness but also by their sense of how patients will respond. Hospital administrators should therefore include clear patient-facing communication and consent guidance as part of any institutional framework for AI use, so that clinicians can apply appropriate tools without worrying about losing patient confidence.

5.2 CONCLUSION

More than three-fifths of the respondents had good knowledge of artificial intelligence in clinical assessment, while more than one-third had poor knowledge. Age and occupation were identified as independent predictors of knowledge. Increasing age was associated with a lower likelihood of good knowledge, and non-physician healthcare professionals had lower odds of good knowledge compared with doctors.

Regarding attitude towards the use of artificial intelligence in clinical assessment, slightly more than half of the respondents had a negative attitude, while slightly less than half had a positive attitude. Marital status, occupation, and knowledge level were the independent predictors of attitude. Respondents with good knowledge were more likely to have a positive attitude, while ever-married respondents and nurses were less likely to do so.

With regard to uptake, more than half of the respondents had ever used an artificial intelligence tool in clinical assessment, with ChatGPT being the most commonly used. Uptake was independently predicted by educational qualification and attitude level, with respondents who had a postgraduate diploma and those with a positive attitude more likely to have used AI.

Regarding level of utilisation among those who had used AI, low utilisation was more common than high utilisation. Attitude was the only independent predictor of high utilisation, with respondents who had a positive attitude towards AI significantly more likely to use it frequently.

Finally, with respect to factors influencing AI use, patient's attitude was the only significant predictor of high level of utilisation, as respondents who reported that patient's attitude did not affect their use of AI demonstrated higher utilisation levels.

Overall, this study shows that while knowledge and initial uptake of artificial intelligence are relatively high among healthcare professionals at UBTH, negative attitudes and perception of patient acceptance continue to limit sustained and routine utilisation in clinical practice.

5.3 RECOMMENDATION

Recommendations to the Government

1. The Federal Ministry of Health, in collaboration with professional regulatory bodies, should integrate structured AI literacy and responsible-use training into continuing professional development programmes for healthcare workers, with targeted inclusion of non-physician cadres and older healthcare professionals.

2. The Federal Ministry of Health and relevant government agencies should expand investment in digital health infrastructure in tertiary hospitals, including reliable internet access, secure electronic systems, and institutional support structures needed for safe AI utilisation.

3. The Nigerian government should support the phased implementation of workflow-integrated AI pilot programmes across federal teaching hospitals, with emphasis on supervised clinical decision-support systems that can be safely incorporated into routine care.

4. Relevant health regulatory authorities should implement periodic monitoring and evaluation of AI use in healthcare settings, including assessment of utilisation patterns, safety concerns, ethical compliance, and barriers to routine clinical integration.

5. The Federal Ministry of Health should incorporate patient-focused education and communication strategies on AI-supported healthcare into national digital health initiatives to improve public understanding, strengthen trust, and support appropriate clinician-patient communication regarding AI-assisted care.

Recommendations to UBTH / Hospital Management

1. Hospital management should organise regular, structured AI training programmes that are tailored to the needs of different professional groups, with particular emphasis on nurses and other non-physician healthcare workers who have shown lower levels of AI knowledge and less favourable attitudes.

2. UBTH should put in place institutional guidelines specifying the safe and appropriate use of artificial intelligence in clinical practice. Clear guidelines will help improve staff confidence, standardise usage, and reduce uncertainty about what is permissible.

3. Hospital administrators should work towards integrating appropriate AI tools into routine clinical workflows in a supervised and structured manner, so that staff have supported opportunities to develop consistent and safe usage habits.

4. UBTH should actively promote interdisciplinary knowledge sharing on AI between doctors and other healthcare professionals, with the aim of reducing the knowledge and utilisation gaps that currently exist across cadres and departments.

5. Hospital management should develop clear frameworks for communicating with patients about the use of AI in their care, including appropriate consent procedures, so that clinicians can use AI tools without concern that doing so will undermine patient trust.

Recommendations to Healthcare Professionals

1. Clinicians should engage with AI as a tool that supports rather than replaces clinical decision-making, while at all times retaining professional judgement and responsibility for the care of their patients.

2. Healthcare professionals should make deliberate efforts to build familiarity with a broader range of AI tools, particularly those specifically designed for clinical assessment, and not limit their engagement to general-purpose platforms such as ChatGPT.
3. Healthcare professionals should actively participate in institutional AI training programmes and contribute their practical experience and professional insight to the development of safe, effective, and context-appropriate AI practices within UBTH.

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APPENDIX I

INFORMED CONSENT FORM

TITLE OF STUDY: UPTAKE AND LEVEL OF UTILISATION OF ARTIFICIAL INTELLIGENCE IN CLINICAL ASSESSMENT AMONG HEALTHCARE PROFESSIONALS IN THE UNIVERSITY OF BENIN TEACHING HOSPITAL

INVESTIGATOR: IDEMUDIA ELOGHOSAVBUMWEN ANGEL

SUPERVISOR: Prof. Andrew I. OBI

FINANCIAL SPONSORSHIP: This research project is self-sponsored.

PURPOSE OF THE STUDY: The purpose of this study is to investigate the knowledge, attitudes, uptake and utilization of Artificial Intelligence among health care professionals in University of Benin Teaching Hospital.

PROCEDURES INVOLVED IN THE STUDY

You are requested to complete a structured questionnaire designed to assess your knowledge, attitudes, uptake, and level of utilisation of artificial intelligence (AI) in clinical assessment and support. The questionnaire will also explore factors influencing the use of AI among healthcare professionals. The information collected will be used strictly for academic and research purposes.

COMPENSATION

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

VOLUNTARY PARTICIPATION

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

RISKS / SIDE EFFECTS

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

BENEFITS

This study aims to generate evidence on the adoption and use of artificial intelligence in clinical practice, which may inform training needs, institutional policies, and strategies for improving healthcare delivery.

CONFIDENTIALITY

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

CONSENT

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

CONTACT INFORMATION:

Idemudia Eloghosavbumwen Angel

Medical Student

Email: angelidemudia28@gmail.com

Tel: +2349052345944

Ethics and Research Committee

University of Benin Teaching Hospital Benin City

Tel: +2347063331337

CERTIFICATE OF CONSENT

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

I voluntarily consent to take part in this study.

Signed_________________

APPENDIX II

DEPARTMENT OF PUBLIC HEALTH AND COMMUNITY MEDICINE

UNIVERSITY OF BENIN, BENIN CITY

UPTAKE AND LEVEL OF UTILISATION OF ARTIFICIAL INTELLIGENCE IN CLINICAL ASSESSMENT AMONG HEALTHCARE PROFESSIONALS IN THE UNIVERSITY OF BENIN TEACHING HOSPITAL

Dear Respondent,

I am a 600-level medical student of the University of Benin conducting a research project to assess the **uptake and level of utilisation of artificial intelligence (AI) in clinical support** among healthcare professionals at the University of Benin Teaching Hospital (UBTH). Kindly complete this questionnaire. All responses will be treated with **strict confidentiality** and used solely for academic purposes.

Thank you for your cooperation.

SECTION A: SOCIO-DEMOGRAPHIC INFORMATION

1. Age (in years): _____________

2. Sex: Male ( ) Female ( )

3. Religion: Christianity ( ) Islam ( ) African Traditional Religion ( ) Others (Specify) ________

4. Ethnic group: Benin ( ) Esan ( ) Etsako ( ) Igbo ( ) Yoruba ( ) Urhobo ( ) Others (specify)_____________

5. Marital Status: Single ( ) Married ( ) Widowed ( ) Cohabiting ( ) Divorced ( ) Separated ( )

6. Occupation: Doctor ( ) Nurse ( ) Pharmacist ( ) Medical Laboratory Scientist ( ) Physiotherapist ( )

7. Designation (in current employment): ______________

8. Department: ____________________

9. Staff Rank: Junior staff ( ) Senior staff ( )

10. Years of Work Experience (in current employment): _________

11. Highest Educational Qualification: Diploma (Post-secondary) ( ) Bachelor’s degree ( ) Postgraduate diploma ( ) Master’s degree ( ) Fellowship ( ) Doctorate (PhD) ( ) Others (specify)_____________

SECTION B: KNOWLEDGE OF ARTIFICIAL INTELLIGENCE IN CLINICAL ASSESSMENT

12. Have you heard of the term Artificial Intelligence (AI) before? (a) Yes ( ) (b) No ( )

If No, skip to Section C (Question 21)

13. If Yes, what is your source of information? **(**Select all that apply**)** (a) Television ( ) (b) Social media ( ) (c) Colleagues ( ) (d) Internet ( ) (e) Hospital training/seminars ( ) (f) Radio (g) Journal ( ) (h) Others (Specify) ______

14. Artificial intelligence refers to (Single response question**)**: (a) Computer systems that can perform tasks that normally require human intelligence ( ) (b) Machines that completely replace healthcare workers ( ) (c) Use of computers only for record keeping ( ) (d) Internet communication systems ( ) (e) Automated machines that function independently without any human input or supervision ( ) (f) General hospital equipment that uses electricity or digital displays ( )

15. Artificial intelligence can be used in healthcare to (Single response question**)**: Support clinical decision-making ( ) Replace doctors and nurses ( ) Eliminate human judgement ( ) Increase clinical errors ( )

16. Which of the following are applications of AI in healthcare? (Select all that apply) Clinical decision support systems ( ) Medical image analysis ( ) Predictive risk assessment tools ( ) Paper-based patient records ( ) AI-assisted clinical documentation ( )

17. Which of the following tools used in clinical assessment are you familiar with as examples of artificial intelligence (AI)? (Select all that apply)

Qure.ai ( ) Claude ( ) Ada Health ( ) Consensus AI ( ) Stratify AI ( ) Sudoku AI ( ) Chat GPT ( ) Beta AI ( ) Zoom ( ) None of the above ( )

18. What is a major benefit of AI in clinical assessment? (Single response question**)**: Improved accuracy and efficiency ( ) Reduced quality of care ( ) Increased workload only ( ) Loss of patient safety ( )

19. A known risk of AI use in healthcare is (Single response question**)** : (a) Bias in algorithms ( ) (b) Faster data processing ( ) (c) Improved workflow ( ) (d) Better documentation ( )

20. For AI to be used safely in healthcare, there must be (Single response question**)**: (a) Ethical and regulatory guidelines ( ) (b) No human supervision ( ) (c) No data protection rules ( ) (d) Complete vendor control ( )

SECTION C: ATTITUDE TOWARDS THE USE OF ARTIFICIAL INTELLIGENCE IN CLINICAL ASSESSMENT

Please pick one answer per row, where SA = strongly agree, A = agree, N = Neutral, D = disagree, SD = strongly disagree

S/N	**STATMENT**	**SD**	**D**	**N**	**A**	**SA**
21	Artificial intelligence can improve the quality of patient care.					
22	The use of AI in clinical assessment can enhance efficiency in my daily work.					
23	I feel confident using AI-based tools to support my					

	clinical assessment					
24	I trust the recommendations provided by AI-based clinical support systems.					
25	AI should be routinely integrated into clinical practice in tertiary hospitals.					
26	I am concerned that AI use may negatively affect patient safety.					
27	AI use in clinical assessment threatens professional autonomy.					
28	Adequate training would increase my willingness to use AI in clinical practice.					
29	AI should support, the clinical judgement of healthcare professionals.					
30	AI should replace the clinical judgement of healthcare professionals.					

SECTION D: UPTAKE AND LEVEL OF UTILISATION OF ARTIFICIAL INTELLIGENCE IN CLINICAL ASSESSMENT

Instruction: Please tick the option that best applies to you.

31. Have you ever used any artificial intelligence (AI)–based tool in your clinic or clinical assessment duties?

    Yes ( )   No ( ) If No, skip to Question 38

32. Which of the following AI-based tools have you used in your clinical practice? (Select all that apply)

    Chat Gpt ( ) Claude ( ) Qure.ai ( ) Stratify AI ( ) ClinicPal ( ) Ubenwa AI ( ) AwaDoc ( ) Ada Health ( ) VisualDx ( ) Others (Specify) ___________________

33. In which areas of clinical practice have you used AI-based tools? (Select all that apply)

    (a) Diagnosis ( ) (b) Treatment planning ( ) (c) Patient monitoring and follow-up ( ) (d) Clinical documentation ( ) (e) Workflow and administrative support ( )

34. How often do you use AI-based tools in your clinical practice? (a) Never ( ) (b) Rarely ( )   (c) Monthly ( ) (d) Weekly ( ) (E) Daily/Almost daily ( )

35. For how long have you been using AI-based tools in your clinical practice? _________(Months)

36. Has the use of AI-based tools improved your quality of clinical care? Yes ( )   No ( )   Not sure ( )

37. Have you ever stopped using an AI-based tool after initial use? Yes ( )   No ( )

    If No Skip to question 38

38. If Yes, What were the reasons for discontinuing AI use? (Select all that apply) (a) Lack of training ( ) (b) Technical and system issues ( ) (c) Poor integration into workflow ( ) (d) Concerns about accuracy or safety ( ) (e) Lack of institutional support ( ) (f) Others (specify)_______________

39. Are you willing to use AI-based tools in clinical assessment? (a) Yes ( ) (b) No ( )

SECTION E: FACTORS INFLUENCING UPTAKE AND UTILISATION OF AI IN CLINICAL ASSESSMENT

40. Have you received any formal training on artificial intelligence or digital health tools?

Yes ( ) No ( )

If No Skip to question 41

41. If Yes, When______________

42. What aspect of artificial Intelligence did you receive training on____________

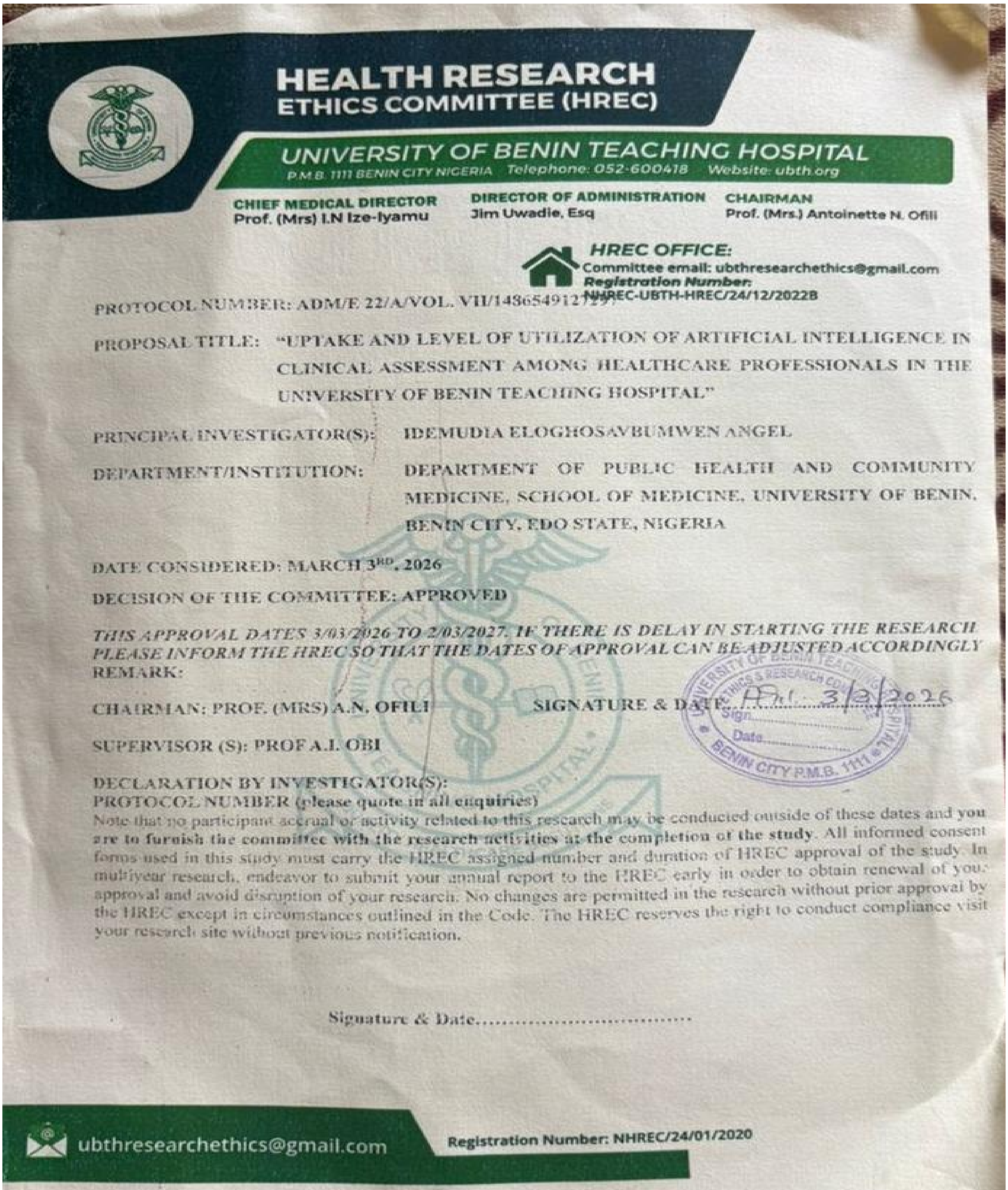
43. Did you get a certification on the training? (a) Yes ( ) (b) No ( )

Instruction: Please tick the either option YES or NO

S/N	STATMENT	YES	NO
44	Unclear ethical guidelines limit willingness to use AI.		
45	AI tools would enhance efficiency in clinical assessment		
46	AI tools are easy to learn and use in clinical practice.		
47	AI tools would integrate smoothly into routine clinical assessment		
48	The attitudes of my patients influence my willingness to use AI		
49	The use of AI tools by colleagues influences willingness to adopt AI in clinical practice.		
50	Adequate infrastructure (such as reliable electricity and internet access) is available to support the use of AI tools.		
51	High workload and time constraints limit the use of AI tools in clinical practice.		
52	Adequate institutional training is available for the use of AI tools.		
53	Concerns about patient data privacy limit the use of AI tools in clinical practice.		
54	Cost or lack of funding limits the use of AI tools in my workplace.		

APPENDIX III

ETHICAL APPROVAL



HEALTH RESEARCH
ETHICS COMMITTEE (HREC)

UNIVERSITY OF BENIN TEACHING HOSPITAL

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

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Registration Number:
NHREC-UBTH-HREC/24/12/2022B

PROTOCOL NUMBER: ADM/E 22/A/VOL. VII/1436549127299

PROPOSAL TITLE: "UPTAKE AND LEVEL OF UTILIZATION OF ARTIFICIAL INTELLIGENCE IN CLINICAL ASSESSMENT AMONG HEALTHCARE PROFESSIONALS IN THE UNIVERSITY OF BENIN TEACHING HOSPITAL"

PRINCIPAL INVESTIGATOR(S): IDEMUDIA ELOGHOSAVBUMWEN ANGEL

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

DATE CONSIDERED: MARCH 3RD, 2026

DECISION OF THE COMMITTEE: APPROVED

THIS APPROVAL DATES 3/03/2026 TO 2/03/2027. 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: 3/3/2026

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.

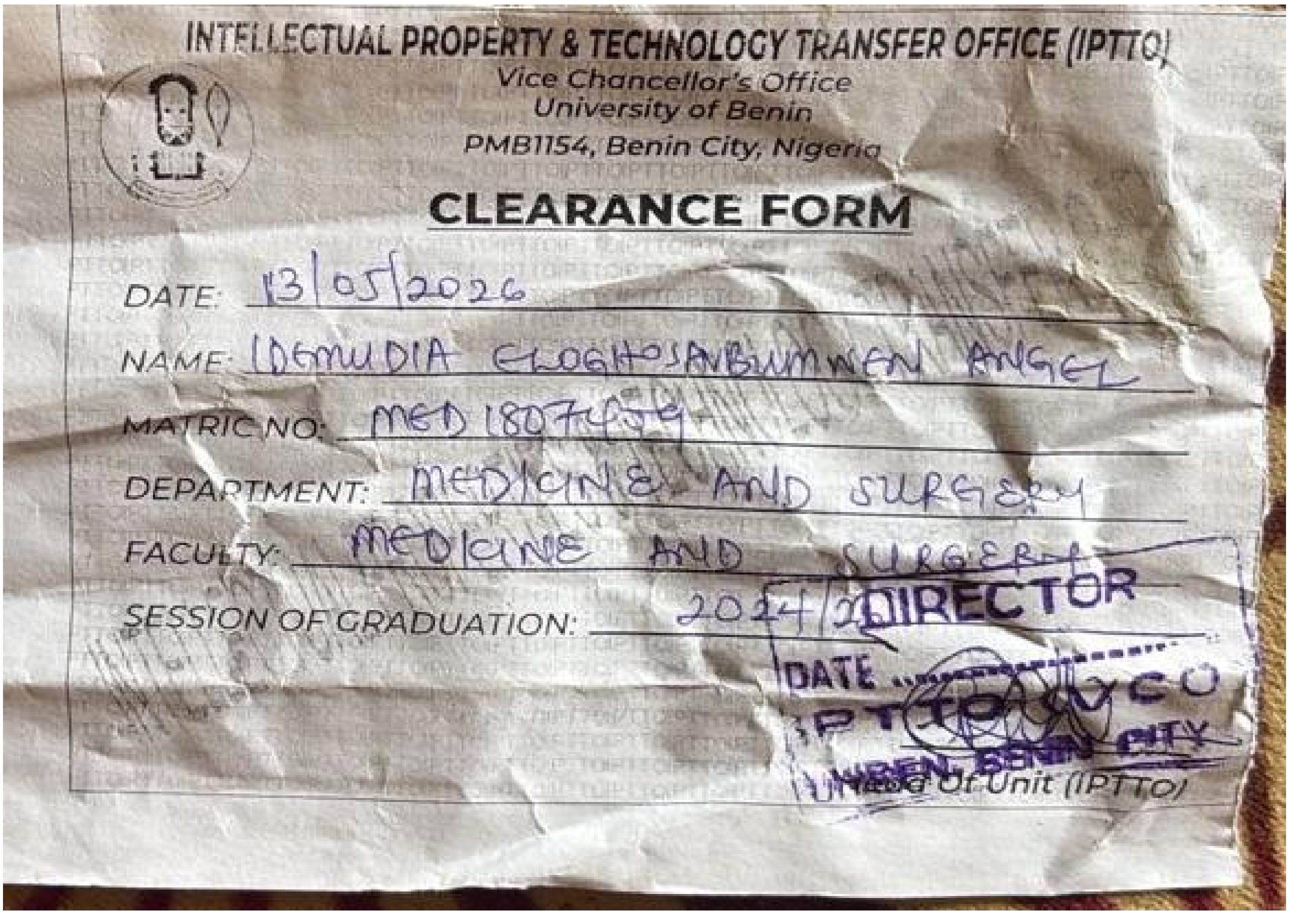
Signature & Date...............................

ubthresearchethics@gmail.com

Registration Number: NHREC/24/01/2020

APPENDIX IV

PLAGIARISM TEST



INTELLECTUAL PROPERTY & TECHNOLOGY TRANSFER OFFICE (IPTTO)
Vice Chancellor's Office
University of Benin
PMB1154, Benin City, Nigeria

CLEARANCE FORM

DATE: 13/05/2026

NAME: IDEMUDIA ELOGHOSAVBIUMWEN ANGEL

MATRIC NO: MED 1807459

DEPARTMENT: MEDICINE AND SURGERY

FACULTY: MEDICINE AND SURGERY

SESSION OF GRADUATION: 2024/20

DIRECTOR
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Head Of Unit (IPTTO)