UNDERGRADUATES' VIEWS ON ONLINE AVAILABILITY OF AI-BASED MENTAL HEALTH INTERVENTIONS IN ENUGU STATE.

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Abstract

This study assessed the undergraduates' views on online availability of AI-based mental health interventions in Enugu state. The survey research design was adopted for the study and the philosophical anchor upon which the work was based was the Health Believe Model. The sample was 384 students selected through multi-stage sampling technique from 12 departments in six faculties of the institutions studied which were University of Nigeria, Nsukka, Enugu State University of Science and Technology and Coal City University. The data generated from the study were analysed with Descriptive statistics of mean and tables with percentage. Findings showed, among other things that the acceptance of online AI-based mental health treatment method by undergraduates in Enugu state is still faced with a myriad of erroneous beliefs and assumptions. It was recommended inter alia that a thorough outreach efforts be embarked upon to inform university students about the online availability, advantages, and efficacy of AI-powered mental health interventions.

Keywords: Ai-based mental health, online availability, intervention, Enugu state

Background of the Study

In the past few years, the marriage of technological advancements and mental health care has undergone significant development, with machine learning also known as AI arising as an exciting instrument for providing care as well as treatments. Pang et al (2018) and Schwab (2017), confirm this when they assert that we are at an important moment in the latest technological era referred to as the internet revolution which involves an integration of various technological sorts. A noticeable instance is a type of technological advances initially acknowledged in 1956 which is artificial intelligence, reveals (Simon, 1991). Artificial intelligent, a machine learning technique that mimics the intelligence of human beings, uses sophisticated software to automatically gather information from data, thereby rendering it simpler and more efficient to detect personalized data trends as well as generate accurate projections from huge Multifaceted information (Ramesh et al., 2004). The integration of mental medical care and technological advances has resulted in widespread curiosity and discussion across researchers, professionals, and members of the public, especially in learning environments like colleges. But for (Kim et.al, 2019), in spite of obvious worries, inclusion of artificial intelligence in healthcare are continuously growing. As mental health specialists, we must acquaint ourselves with artificial intelligence, grasp its present and potential functions, and be ready to collaborate with artificial intelligence as it flows into the medical environment. Although intelligent devices are not likely to entirely substitute healthcare workers, they are becoming more frequently utilized to assist

with medical choices (Hengstler et al, 2016; Topol, 2019; Topol, 2019). Human intelligence is constrained by its ability to learn, access to scientific resources, and reality, whereas artificially intelligent machines can swiftly generate data collected from an infinite number of health-related materials. To maximize artificial intelligence's possibilities, big data sets that can be technically examined are perfect, uncovering developments and links about human conduct and habits (Wang et al, 2016) that are frequently difficult for individuals to gather. These investigations also show that using artificial intelligence algorithms to analyse mental health big data is extremely important for the growth and advancement of the field of mental healthcare (Noorbakhsh-Sabet et al., 2019).

Furthermore, artificial intelligence has the capacity to transform our diagnosis as well as comprehension of mental health conditions (Bzdok et al, 2018). A person's distinct bio-psycho-social identify makes it ideal for clarifying his or her overall mental state (Jeste, 2019). Using artificial intelligence approaches allows for the development of more accurate prediagnosis evaluation instruments and risk estimation algorithms for assessing someone's genetic makeup for, or likelihood of developing, psychological disorder (Shatte, 2019).

Machine learning techniques can be utilized to thoroughly generate value from many different sources of information, allow a deeper comprehension of the population-level incidence of neurological ailments, identify natural processes or risk/protective elements, supply equipment for tracking improvement in therapy and/or compliance with medications, supply distant therapeutic sessions, or give smart self-evaluations to figure out the degree of mental disorder as well as help mental health professionals concentrate on the human dimension of healthcare, which are achievable only by means of a bond between clinicians and their patients (Kim et.al, 2019; Topol, 2019).

Interestingly, artificial intelligence technologies are now widely used in a variety of areas, including automation, graphic and speech recognition, natural language processing, and skilled systems (Sheikhtaheri et al., 2014; Trivikram et al., 2017; Yu et al., 2018; Xiang et al., 2020). Furthermore, AI has shown ensuring usage in the diagnosis, medication, and prognosis prediction of neurological conditions (Gao et al., 2018; Abd-Alrazaq et al., 2023Additionally, artificial intelligence can be either explicitly or implicitly used in smart technological treatments (Minerva and Giubilini, 2023). For instance, artificial intelligence is employed together with electronic medical records, brain scans, sensor-based surveillance equipment, and networking sites to forecast, categorize, or subgroup psychological conditions and suicide, resulting in measures for preventing and treating of mental health ailments (Lee et al., 2021). Also, the swift development of innovations such as neuroimaging, messaging apps, cell phones, as well as mobile devices has allowed mental health professionals to rapidly access enormous quantities of data (Benoit et al., 2020). Similarly, As AI swiftly alters the field of healthcare, scholarly study on the connection of AI and undergraduate mental health has risen dramatically in the past few years (Gil et al., 2022; Wang, 2023).

Although artificial intelligence has recently become increasingly popular in healthcare for physical health uses, the field of mental health is being too slow to fully embrace artificial intelligence (Jiang et al, 2017; Miller et al 2018). Mental health professionals are more practical and patient-centered in their professional lives than the majority non-psychiatric professionals, depending more on "softer" abilities, such as developing bonds with patients as well as monitoring how they behave and feel (Gabbard & Crisp-Han, 2017). Regardless of the fast growth of clinical psychology and psychiatry in recent years, diagnostic inconsistency and unclear prognosis remain. Mental and pharmaceutical therapies usually prove successful in only 30 to 50% of patients (Stein et al., 2022; Hoeflich et al., 2023).

A large number of patients continue to face challenges in terms of prompt identification and remedy (Colizzi et al., 2020). As a result, the area of mental health among undergraduates demands multifaceted data-driven diagnosis and prediction in order to give targeted therapies and interventions (Torous and Keshavan, 2018), all of which necessitate operational analysis of large amounts of data.

Additionally, integrating artificial intelligence into mental health custody is fraught with complications and debates. Ethical aspects, worries about confidentiality, effectiveness, and societal significance are just a few of the numerous variables that influence the conversation about artificial intelligence-based solutions. Furthermore, as major players in this conversation, undergraduate students' views, opinions, and demands have a significant impact on the acceptance and execution of such measures. Although, over time, studies indicate an ongoing spike in the incidence of depression and anxiety signs among undergraduates (Liu et al., 2019; Lipson et al., 2019). On a worldwide scale around 31 percent of students in higher education receive positive results from mental health disorder tests (Auerbach et al., 2018), drawing prevalent societal interest. The circumstances that contribute to mental health ailments in undergraduates are numerous, and the pathological development of prevalent mental conditions like depression and anxiety is complicated. It is difficult to ascertain their causes, diagnosis, prognosis, and therapeutic procedures. (Alexopoulos, 2005; Greenberg et al., 2012; Slimmen et al., 2022). The fact remains that as artificial intelligence is starting to be used in healthcare environments (Jiang et al, 2017) We remain far removed from habitual implementation of artificial intelligence for medical purposes because the costs are much higher compared to the effects of the artificial intelligence that promotes our contemporary amenities (Hengstler et al, 2016).

Online AI-based mental health interventions have grown in popularity, with patients receiving assistance, treatments, and information through artificial intelligence. Here are some noteworthy interventions as enumerated by Sutton, (2024):

Wysa: This AI-powered chatbot assists those dealing with anxiety, despair, and distress. This scientifically established instrument offers both instant assistance as well as long-term training, providing a secure space to discuss problems and concerns.

Happify: This important software employs artificial intelligence to assist patients and provides scientific exercises and puzzles that assist relieve tension and improve their overall health. The software employs well-established strategies from therapeutic psychology, psychological treatment, and meditation.

Rootd: This is an excellent instrument for understanding where fear stems from and for managing and overcoming terror episodes. At the touch of a button, the software assists an individual experiencing a panic attack by either confronting the panic or seeking a location of calm.

Sanvello: This software supports individuals' mental wellness through caring for oneself, assistance from others, instruction, and rehabilitation. The software is built on Cognitive-Behavioural Therapy and meditation procedures, and it is adapted to each of the client's specific demands.

Aside the ones listed by Sutton above, Additional interventions include:

Woebot: This is a cognitive-behavioural therapy (CBT) with a set of approaches for helping individuals maintain their state of mind. Woebot assists people acquire knowledge of emotional regulation via discussions and promotes mood surveillance and control, including features like attitude evaluation, progress review, gratitude writing, and mindfulness exercises Woebothealth.com (2024).

Ginger Offers immediate mental wellness care via AI-powered chatbots and links consumers with real therapists for further help. It enables clients to communicate their personal difficulties with professional therapists, mental health professionals, and master's-level emotional wellness trainers through text, chat, or video. The program, which is open 24/7 and covered by employer-provided healthcare coverage, engages numerous physicians and serves more than 200 thousand individuals. Ginger evaluates patient results using established diagnostic methods for depression and anxiety (Faught, 2019).

Youper: An online artificial intelligence-powered application that guides clients via talks using CBT concepts to improve their emotional and mental wellbeing. Youper uses neuroscience and AI to figure out consumers' psychological requirements and take part in realistic interactions (Youper, 2024).

These online artificial intelligence-based therapies demonstrate possibilities of rendering

behavioural health treatments more readily available and individualized, but there are continued worries regarding the erosion of human sympathy, data security, and the possibility that artificial intelligence can perpetuate inherent prejudices. Further studies and improvements are required to overcome these issues and enhance the use of online artificial intelligence-powered mental health interventions.

From the Nigerian environment, Enugu State serves as a small example of this worldwide development, with the discussion of artificial intelligence-based mental health treatments around undergraduates receiving more media coverage. Enugu State, located in Nigeria's south-east, boasts an enviable educational scenery, which includes several colleges and universities responding to a broad student body. As mental health worries within undergraduates gather traction, there is an increasing awareness of the necessity for new methods to addressing these problems. However, for this background, artificial intelligence-based measures have become known as a promising opportunities, with the ability to transform mental health care through delivering modular, customized, and affordable remedies. This research seeks to dig deeper into the diverse range of perspectives held by undergraduates in Enugu State on artificial intelligence-based mental health solutions. Also, through investigating their viewpoints, beliefs, and worries, this study aims to add to an improved comprehension of the fusion of technology and mental health in Nigerian educational institutions. By doing this investigation, we are interested in shedding light on the possibilities and difficulties built in using artificial intelligence to promote the emotional stability of undergraduates, eventually promoting subsequent efforts as well as regulatory choices in the field of mental health treatment.

Statement of the Problem

The use of the latest online artificial intelligence-powered interventions to enhance mental health treatments has gained popularity in the past few years, especially among undergraduates who frequently experience specific stressors and challenges. Nevertheless, in the midst of this reality, there is still a large knowledge vacuum regarding the student's perception of these online artificial intelligence-based measures, especially among university students in Enugu State, Nigeria.

Thus, the purpose of the research is to ascertain how undergraduates view online AI-based mental health programs among Enugu State undergraduates, with an emphasis on finding out inherent obstacles, worries, as well as approval factors that may affect the uptake and efficacy of such programs within this population. This study aims to close these information voids and advance the creation of online AI-based mental health therapies that are efficient, culturally appropriate, and customized to the demands and tastes of Enugu State university students.

Objectives of the Study

The objectives of the study are to ascertain:

1. The level of awareness of the presence and accessibility of online artificial intelligence-based mental health interventions among undergraduates in Enugu state.
2. The factors hindering the acceptance of online artificial intelligence-based mental health interventions among undergraduates in Enugu state.

Literature Review

Jin, et al. (2023) looked at Artificial intelligence in mental healthcare: An overview and future perspectives. The work showed that artificial intelligence is causing a crucial change in the field of mental health, but success has been impeded by the absence of broad, excellent diverse data collections. Nevertheless, the latest advances in digital health are a promising plus to the computational and medical toolkits, increasing the availability of care and facilitating public health tracking.

Similarly, Chen, et.al. (2024) studied Artificial intelligence significantly facilitates development in the mental health of college students: A bibliometric analysis. Documents on artificial intelligence and undergraduate mental health were obtained from the Web of Science core database. The spread of materials was examined to determine the most common output. VOSViewer was used to examine data on countries, contributors, journals, and keywords, with the goal of discovering

partnership structures, disciplinary design, research areas of greatest need, and developments. Findings showed that, the root causes of mental health problems are numerous, and conventional psychological study frequently employs upward theoretically based methods that necessitate clearly defined theoretical hypotheses verified by way of gathering information. However, unlike typical behavioural study approaches, future artificial intelligence-driven investigation can take a bottom-up, data-driven strategy for identifying associations among factors, displaying previously unknown causes of university student mental health challenges. So, this approach is better suited to the development of smart apps for intervention and prevention with a higher efficacy. Also, the broad combination and growth of artificial intelligence with psychological study entails combining mental health with expertise from fields like biology, society, information, and computer science. This consists of developing predictive computer programs, paying particular attention to automated projections, and ensuring ethical oversight when using large amounts of data in the field of mental health for the betterment of a wider audience.

In another development, Eze, et al. (2020), studied the public perception and implications of mental illness in Enugu urban, Enugu state, Nigeria. The philosophical underpinning that guided the study was that of attribution theory. The study utilized across sectional survey design. A sample size of 300 respondents was arrived at with the aid Fisher's formula. The results revealed that the general impression of mental health conditions in Enugu City was negative, with a focus on neglect and mistreatment. Furthermore, it was discovered that the consequences of such attitudes included abandoning of the mentally ill as well as the widespread belief that they are an issue for the community. The study went ahead to suggest among others, the need for an intensive re-education of Enugu urban inhabitants on mental health challenges.

In the same vein, in trying to ascertain the understanding of the genesis of their psychological condition, as well as the initial treatment they used and why, Aniebue & Ekwueme (2009), conducted a research on health-seeking behaviour of mentally ill patients in Enugu, Nigeria. A total of 397 patients undergoing rehabilitation at Enugu's neuropsychiatric medical facility were selected in succession. Findings revealed that the patient's views on the source of their illness frequently showed a belief in diabolical and supernatural powers. Also, Gender, level of education, attributing mental health issues to a rational cause, and staying in a city all had an important effect on the acceptance of a psychiatrist solution as the initial therapeutic choice. The study concluded that incorrect assumptions about the cause of mental disorders are still prevalent among those with mental illness in Nigeria. As a result, psychiatric consultation is rarely used at the outset, particularly in remote regions.

Theoretical Framework

This study is anchored on the Health Believe Model. Propounded by Hochbaum & Rosenstock in 1952, Health Belief Model (HBM) is a well studied model of health behaviour. As social psychology model for health behaviour modification, the health belief model (HBM) was created to clarify and project behaviours connected to health, especially when it comes to using medical treatments (Siddiqu et al, 2016; Janz & Marshall, 1984). Someone's ideas about avoiding illness, preserving health, and aiming for good health are also included in the health belief model (Wang, 2024). According to the HBM, a person's self-assurance, perceptions about health issues, and perceptions of the advantages and disadvantages of taking action all contribute to their willingness or inability to get involved in actions that promote health. The presence of a stimulus, or prompt to action, is also necessary for the health-promoting behaviour to be triggered (Rosenstock, 1974).

By focusing on different facets of the model's central concepts, the HBM has been utilized to create successful interventions to alter health-related behaviours (Carpenter, 2010; Rosenstock et al, 1988). By offering awareness about the rate and frequency of disease, personalized risk assessments, as well as details regarding the adverse effects of disease, therapies built on the HBM may seek to enhance the sense of susceptibility to and perceived severity of a medical problem (Glanz et al., 2008). By figuring out prevalent believed obstacles, offering motivations to engage in healthy habits, enlisting the assistance of others

or additional help, and supplying facts regarding the effectiveness of different behaviours in minimizing the risk of ailments, treatments can additionally attempt to change the cost-benefit analysis of involving in a health-promoting habit like, boosting perceived advantages and reducing perceived obstacles.

In addition, therapies grounded in the Health Belief Model (HBM) could offer indicators to action that prompt and motivate people to adopt healthy habits. Providing instruction in particular health-promoting behaviours, especially for challenging lifestyle adjustments (such as altering one's diet or level of exercise, or following a convoluted prescription schedule), is another method that treatments may seek to increase self-efficacy. Therapies might be focused on changing society norms or individual behaviour for instance, working individually with people to improve involvement in health-related behaviours (Stretcher & Rosenstock, 1997).

The HBM makes an effort to forecast behaviour related to health based on specific belief patterns. Three areas can be used to categorize a person's motivation for engaging in a health behaviour: the probability of action, changing circumstances, and personal views. The value of being healthy to a person, perceived seriousness, and a sense of vulnerability are all elements that influence how they see sickness.

Cues to action, a sense of danger, and social background are examples of moderating factors. The perceived advantages of following the advised course of action less the perceived obstacles results in the probability of action. These elements work together to produce a reaction that frequently translates into the possibility of that conduct happening.

(Janz & Becker, 1984 and Rosenstock et al, 1988) cited in (Kerry & Elizabeth, 2020).

This theory is appropriate for this study in the sense that that the acceptability of AI-based mental health treatment or otherwise, is largely dependent on preconceived thought about mental health and the treatment pattern they believe is best suited for it.

Methodology

This study employed the survey research design. A survey refers to the research design where opinions of respondents are sought to formulate data that proffer answers and solutions to a set of research problems. According to Ezeah and Asogwa (2013, 302), "survey method is a very good and reliable method of gathering data and it can be used to study the behavioural pattern of a population". Survey was adopted in this study because it is used to elicit data regarding the opinions of university students on AI-based mental health interventions in Enugu state.

The population of this study comprises all the students in the three universities- University of Nigeria Nsukka (UNN), Enugu State University of Science and Technology (ESUT), and Coal City University (CCU) which were used as representative universities for federal, state and private universities respectively in Enugu state. The total population for this study is 93,299 students drawn from the three universities. The figure was arrived at by summing up the population of students from the universities. As obtained from the academic planning unit of these universities, UNN has 42,300 students constituting 45.4%; ESUT has 50,000 students constituting 53.6%, while Coal City University has 999 students constituting 1% of the population.

Three hundred and eighty three (383) respondents which made up the sample for this study was approximated to 384. By utilizing the Australian calculator to calculate sample size, this result was reached. It is essential to determine a sample size since it was impractical to investigate every component of the population for this study. The sample was picked from the university students aged 18 and 45 years in 300 and 400 levels in two faculties and one department each of the faculties in the universities under study by utilising the multi-stage sampling technique. Thus, in UNN, under the faulty of Arts, Mass Communication department was chosen. While in the faculty of Social Sciences, Political Science department was chosen. In ESUT, the faculty of Law had the department of Public Law, picked, while in the faculty of Natural Sciences, the department of Applied Biochemistry was selected. In CCU, the faculty of Natural and Applied Sciences, the department of Mathematics and Computer science was picked, whereas in the faculty of Arts, Social and management Sciences, the department of Economics was selected. With the adoption of a proportionate sampling technique, each department in the six faculties

chosen, had 32 respondents, making it a total of 384 sample size. Below is the table showing how the respondents were picked:

SCHOOLS	FACULTIES	DEPARTMENTS
UNN	Arts	Mass Communication
	Social Sciences	Political Science
ESUT	Law	Public Law
	Natural Sciences	Applied Biochemistry
COAL CITY UNIVERSITY	Natural and Applied Sciences	Mathematics and Computer science
	Arts, Social and management Sciences	Economics

The research instrument for this study was the questionnaire. The questionnaire had two sections; the first one covered the demographic characteristics of the respondents while the second one contained items that addressed the research questions. A four-point Likert scale of strongly agree, agree, disagree and strongly disagree with assigned values of 4, 3, 2 and 1respectively were also adopted for ease of statistical analysis, while the instrument was validated by three experts in research who are lecturers in the Department of Mass Communication, University of Nigeria, Nsukka. Also, the instrument got a Cronbach's Alpha coefficient of 0.709, which indicated that it was 71% trustworthy, according to the aforementioned reliability result. A total internal consistency of 0.71 indicated that the research instrument was reliable.

Descriptive statistics of mean and tables with percentage was employed to analyse the research questions. The options in the Likert scale were given the following statistical values: 4 points for Strongly Agree (SA), 3 points for Agree (A), 2 points for Disagree (D) and 1 point for Strongly Disagree (SD). Thus, the benchmark for the study was, 2.5.

Presentation of Findings

Research Question One: What is the level of awareness of the presence and accessibility of online artificial intelligence-based mental health interventions among undergraduates in Enugu state?

Responses on the level of awareness of online availability of artificial intelligence-based mental health interventions among undergraduates in Enugu state

ITEM STATEMENTS	SA	A	D	SD	MEAN	RATING
I have an online/internet enabled gadget (Phone, Laptop, Tabs, Etc.)	358	22	-	-	3.9	Accepted
I am on an online platform	345	31	4	-	3.8	Accepted
I am active online	322	34	24	-	3.8	Accepted
To what extent are undergraduate students in Enugu state aware of artificial intelligence-based mental health interventions?						
a. Fully Aware	116	208	45	11	3.1	Accepted
b. Aware	217	141	9	13	3.4	Accepted
c. Undecided/ Unsure	54	76	140	110	2.2	Rejected

d. Unaware	6	10	83	281	1.3	Rejected
e. Largely Unaware	8	12	158	202	1.5	Rejected
How often do you come across artificial intelligence-based mental health interventions online?						
a. Very often	301	53	26	-	3.7	Accepted
b. Often	199	83	65	33	3.1	Accepted
c. Rarely	42	52	175	111	2.1	Rejected
d. Never	12	32	148	188	1.7	Rejected
Which online platform do you see more artificial intelligence-based mental health interventions online on?						
a. Internet	155	123	69	33	3.1	Accepted
b. Social media	168	102	81	29	3.1	Accepted
c. Blogs	162	125	62	31	3.1	Accepted
d. Online news outlets	65	91	182	42	2.5	Accepted

The findings of the study on the level of awareness of undergraduates in Enugu state of the online availability of artificial intelligence-based mental health interventions can be seen in the table above. The result reveals that the respondents are aware of the online availability of artificial intelligence-based mental health interventions. This can be linked to the fact they are internet savvy and are also at an impressionable age with inquisitive minds.

The results above are also corroborated by (Chen & Jiang, 2019 and Wang et al., 2020) who asserted that university students are often chosen as participants for behavioural studies, mainly because researchers from institutions or study centres have easier means of reaching them. Furthermore, undergraduates typically possess adequate intellectual capacities and an eagerness to cooperate, which allows them to swiftly get involved in and carry out studies, thus encouraging the advancement of scientific inquiry.

Research Question Two: What are factors hindering the acceptance of online artificial intelligence-based mental health interventions among undergraduates in Enugu state?

	SA	A	D	SD	M	R
The issue of data security.	318			9		Accepted
The belief that mental health illness is as repercussion.	201			12		Accepted
The belief that mental health issues has no permanent solution.	189			18		Accepted
Lack of trust and confidence in orthodox treatment regarding mental health disorder.	123			84		Accepted
The belief that mental health problem is spiritual.	188			12		Accepted
The notion that mental health cases are hereditary and bound to happen.	179			23		Accepted

Lack of adequate and proper sensitisation on mental health challenges.	123			08		Accepted

Results from the table above reveal the factors hindering the acceptance of artificial intelligence-based mental health interventions among undergraduates in Enugu state. The number five item statement that pointed out the belief that mental health problems are spiritual is in alignment with Aniebue & Ekwueme (2009)'s revelation that psychiatrist patients always held the opinion that the source of their illness is diabolical and supernatural.

Also,(Jin, et al, (2023), held the same view in their report concerning data security when they stated that the progress and revolution brought about by artificial intelligence in the field of mental health is being hampered by the lack of broad, excellent diverse data gatherings.

Lack of correct orientation of course, is part of a major setback to the acceptance of artificial intelligence-based mental health interventions among the respondents as the findings in the table above also reveal. This is in line with the findings of Eze, et al. (2020) which reported that the general impression of mental health conditions in Enugu City was negative.

Conclusion and Recommendations

The online presence of artificial intelligence-based mental health interventions is quite a huge breakthrough in the area of mental health with the enormous benefits it holds in the treatment of the illness. However, the acceptance of this treatment method by undergraduates in Enugu state is still faced with a myriad of erroneous beliefs and assumptions like the findings from the study showed.

Following the findings of the study, the researcher makes these recommendations:

1. A thorough outreach efforts should be embarked upon to inform university students about the availability, advantages, and efficacy of AI-powered mental health interventions. This can be achieved through a variety of channels, including social media, campus websites, as well as seminars.
2. Preference should be given to patient's confidentiality and safety via the implementation of robust data safety strategies and adhering to applicable regulations like the General Data Protection Regulation (GDPR) alongside the Nigerian Data Protection Regulation (NDPR).
3. The ministry of health should works together with higher education institutions as well as functioning mental health clinics in Enugu State to incorporate AI-powered treatments into their services. This is an opportunity to connect with a wider population and guarantee consistency of care for students who might need assistance besides digital means.
4. Health ministry should work out modalities to increase the accessibility of AI-based mental health interventions, especially in remote locations where internet connection is potentially scarce. This might require collaborating with community-based centres or delivering interventions through offline means.

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