IMPROVED DEPRESSION SYSTEM USING NEURO-FUZZY INFERENCE SYSTEM

N. B. Uchechukwu [(1)]*
I. R. Omovorai [(2)]*

Received: 22/01/2025
Revised: 09/03/2025
Accepted: 10/03/2025

[1] Department of Computer Science Federal University of Petroleum Resources, Effurun Delta State – Nigeria.
[2] Department of Computer Science Federal University of Petroleum Resources, Effurun Delta State – Nigeria.
*Corresponding Author's Email: Nwozor.blessing@fupre.edu.ng, roseiledia@yahoo.com

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N. B. Uchechukwu
Department of Computer Science
Federal University of Petroleum Resources, Effurun Delta State
Nwozor.blessing@fupre.edu.ng

I. R. Omovorai
Department of Computer Science
Federal University of Petroleum Resources, Effurun Delta State
roseiledia@yahoo.com

Abstract— The place of depression in impeding organisational productivity cannot be overemphasised, as this silent and almost neglected mental health disorder has caused loss of revenue, loss of jobs, death, and risk of suicide in the workplace. Depression is a prevalent and dangerous medical condition that has an adverse effect on one's emotions, thoughts, and behaviour. Some of the basic symptoms of depression include sadness and/or a loss of interest in once-enjoyed activities, and it can impair the capacity of an individual to perform both at work and at home and result in a range of emotional and physical issues. With an estimated 6.7%, which accounts for one in fifteen adults suffering from depression in any given year. Furthermore, 16.6% of people, or one in six, will at some point in their lives experience depression; therefore, the need for a system to accurately detect the disease in a timely manner. This paper, therefore, proposes the development of a workplace depression detection system using a mobile application development platform. The proposed system was developed in Android Studio with Java and Kotlin using the object-orientated analysis and design (OOAD) methodology, which is a flexible software development paradigm that takes an object-orientated approach. The new mobile apps have great potential in addressing the burden of workplace depression with the aim to intervene with at-risk people, particularly in the workplace, which is crucial to their effectiveness, as the system shows high accuracy in identifying depression, and it is portable, secure, and user-friendly, providing an amazing user experience (UX). The system can be implemented and used in the workplace, making it accessible to all and thereby enhancing employee efficiency and productivity.

Keywords— Expert System, Depression, Workplace, Mobile App, Severity, UX, UI.

I. INTRODUCTION

The prevalence of mental health disorders has become a major concern in the public health sector over the past ten years. Individuals suffering from severe mental disorders are more likely to engage in unusual behaviours, such as acts of violence, which can cause harm to both themselves and those around them. An estimated 450 million people worldwide suffer from psychological disorders, of which 322 million are depressed; the majority of these people, according to estimates from the World Health Organisation, reside in East Asia and the Western Pacific region [1]. According to World Health Organisation (WHO) projections, depression is expected to rank as the second most prevalent condition globally by 2020. The importance of mental illnesses, particularly depression, has been demonstrated by data from these publications. Depression affects one in five women and one in twelve men at this time. Not only are adults frequently affected by depression, but children and adolescents also experience it. Worldwide, 5% of adolescents and 2% of youngsters suffer from depression, and in many cases, the cause of their illness is still unknown [2]. Reports that are now available indicate that depression is rising at a concerning rate. Emotions, behaviour, and physical health are all impacted by this condition. Suicide is a possible consequence of depression when it has a strong impact on a person. The primary issue is that over 50% of individuals with depression might not be aware that they have the illness or frequently get the wrong diagnosis of another condition [3]. Most nations now accept that mental health issues, including depression and anxiety, can be problematic in the workplace. The worldwide economic impact of mental illness was predicted to be US$2.5 trillion in 2010 and US$6.1 trillion in 2030 using a human capital approach; absenteeism and presenteeism accounted for the majority of this burden [4].

Employers who help employees with mental health disorders and encourage good mental health are more likely to see a decrease in presenteeism, which implies a lower level of productivity while the worker or staff is present at work, and absenteeism, which is a reduction in the number of days missed from work [5]. [6] reviewed the relationship between worker productivity and mental health, and the study indicated a positive correlation between the prevalence of mental health problems and absenteeism, especially short-term disability absences. In many spheres of life, stress and depression are prevalent conditions. Stress can reduce productivity or lead to depression if it is not controlled. Stress is not a prerequisite for depression to occur, which implies that depression can occur devoid of stress [7].

Mental illness, sometimes referred to as mental health diseases, is a physical brain ailment that may have an impact on mood, behaviour, and thought processes. It also results in a depletion of interest and energy, raises the risk of suicide, and can negatively impact relationships and job performance. Approximately 13% of children, 46% of teenagers, and 19% of adults worldwide experience mental illness on an annual basis [8]. Depressive disorders were also shown to be the most prevalent mental health issue among most workforce sectors. It has been seen that workplace policies that facilitate access to evidence-based care for employees lead to a decrease in absenteeism, disability, and poor productivity [9]. Businesses and organisations suffer indirect losses due to depression annually, which results in reduced productivity, absenteeism, and even lower job retention across a wide range of industries. The estimated loss of over $2.5 trillion USD annually is a great blow to the global economy with the attendant loss of valuable man-hours and death. The level of productivity within organisations with employees suffering this form of mental health disorder is always on the decline. With the variance in the symptoms, it has become more difficult to ascertain the presence of the disease, especially in the workplace, and the application of information technology tools has also brought in a new lease of life to address the

menace. The major limitation still remains the fact that an employee will have to skip work to be attended to in the hospital for issues of mental health disorder, which also contribute to a high level of organisational losses. This paper therefore proposed the development of an enhanced depression detection system using a mobile application development framework to enable easy checks and early detection of depression in employees to ascertain their mental health status and stability.

A. Theoretical Framework

Many employers have launched programs to address employee stress. However, I doubt that many companies can identify and describe the specific stress theory that underpins their project. Currently, five theories have been recognised as the underlying causes of workplace stress and depression. Each of the hypotheses has been thoroughly examined and has its own set of research findings or evidence to support its existence. To comprehend depression and stress in the workplace, one must first grasp the five theories and their applicability in the workplace with respect to their impact on employee efficiency and productivity. These theories include

- Demands – Control Theory,
- Demand – Control - Resources Theory,
- Effort – Reward Imbalance Theory,
- Conservation of Resources Theory,
- Person - Environment Fit Theory

The demand-control theory, which explains how job features affect employees' psychological well-being and productivity, is prominent among these theories. It also shows how the high workload, role ambiguity, and work-related stress of an employee can cause stress and depressive episodes.

II. CONCEPTUAL REVIEW

This section reviews the concepts of depression and the application of information and communication technology tools to mitigate and detect the impact of mental health disorder and depression in the workplace, taking into consideration the concepts of expert systems and their integration and application in the mobile application framework for managing mental health disorder.

A. Overview of Mental Health Disorder

Mental health encompasses more than just the absence of mental diseases. The World Health Organisation, in her definition of health, emphasises the positive aspects of mental health: “Health is a state of complete physical, mental, and social well-being, not merely the absence of disease or infirmity.” Mental health concepts include subjective well-being, perceived self-efficacy, autonomy, competence, intergenerational reliance, and the ability to reach one's intellectual and emotional potential. It is characterised as a condition of well-being in which individuals recognise their skills, cope with stress, work productively, and contribute to their community. Mental health aims to improve individual and community competencies and enable people to attain self-determined goals. Mental health should be a priority for everyone, not only those suffering from mental disorders [10]. Mental health disorders are a collection of mental health conditions that influence people's moods, thinking, and conduct. Mental health issues do not only affect the individual. They affect the entire community. The cost of excluding people with mental health issues from active participation in communal life is significant. Exclusion frequently leads to decreased productivity and lost human potential. It is a clinically significant disruption in an individual's behaviour, emotion regulation, or thought processes that is indicative of a mental disorder. Usually, it is linked to distress or impairment in critical domains of functioning. There are numerous varieties of mental illnesses. Mental health issues is another name for mental disorders. The latter is a more general phrase that encompasses psychosocial disabilities, mental disorders, and (other) mental states linked to substantial distress, functional impairment, or self-harm risk [11].

B. Common Mental Health Disorder

Mental illness is now more prominent than ever in public health discussions. A recent study indicates that mental illness is more widespread and serious than previously thought. In developed countries like the United States and the UK, people are no longer told to "toughen up" or "just don't think about it." Instead, they are treated with the same haste and care as if they were physically injured. [12]. According to the Centre for Disease Control and Prevention (CDC), approximately one in every five young people between the ages of 13 and 18 suffers from a major mental illness, either now or at some time in their lives. Approximately one in every 25 adults in the United States suffers from a significant mental illness, such as schizophrenia, bipolar disorder, or major depression [13].

The three most common diagnoses are anxiety disorders, depression, and post-traumatic stress disorder (PTSD). These three diseases account for approximately 30% of all mental illness diagnoses in America. While they have many of the same features, they are radically distinct from one another.

C. Anxiety Disorders

Anxiety disorders are defined by persistent feelings of severe anxiety or worry. This group of conditions includes generalised anxiety disorder, panic disorder, social anxiety, and other phobia-related worries. According to [14], anxiety disorders are the most prevalent or commonly occurring mental disorders that affect an estimated 20% of adults annually, generally producing a sense of fear, worry, and a constant feeling of being overwhelmed. They cover a range of illnesses where the primary disruption of mood or emotional tone is severe or pathological worry. Anxiety is characterised by disruptions in mood, thinking, conduct, and bodily functions. It can be thought of as the disordered equivalent of natural fear. The anxiety disorders include obsessive-compulsive disorder, panic disorder (with or without a history of agoraphobia), post-traumatic stress disorder, generalised anxiety disorder, specific phobia, social phobia, and acute stress disorder. Moreover, there are disorders resulting from general medical illnesses, substance-induced anxiety disorder, and adjustment disorders with anxiety symptoms [15].

D. Post-Traumatic Stress Disorder (PTSD)

The complex disease known as post-traumatic stress disorder (PTSD) is brought on by exposure to one or more traumatic events, such as those that occur during a conflict, acts of terrorism, natural or man-made disasters, and violent crimes against individuals, such as rape, mugging, domestic abuse, and accidents. People who suffer from PTSD frequently experience emotional numbness and have a recurring dread memory. Because PTSD is frequently associated with substance addiction and severe depression, untreated PTSD can be fatal [16].

According to [17], trauma is a significant risk factor for both mental and physical health issues. Excessive stress exposure can lead to PTSD, a condition characterised by a range of mental and physical symptoms. Diagnosing this condition might be problematic due to its complex pathophysiology and co-existence with other mental diseases. Exposure to stressors, together with peritraumatic circumstances, is the primary cause of PTSD development and progression. A variety of factors can impact the disease's natural course and response to stressors. Understanding the condition allows for preventive and convenient approaches to improve quality of life. It is important to note that variations in PTSD diagnostic criteria and definitions may make it more difficult to identify and diagnose the condition accurately, which may impede prompt and efficient treatment. Furthermore, it has been shown that short-term and declarative memory deficits may increase a person's risk of developing PTSD.

E. Depression

Depression is a medical condition characterised by a decline in mood. In addition, there are unpleasant emotions, a poor sense of humour, distress and panic episodes, a decline in the functioning of different psychic and cognitive abilities, a propensity for seclusion, apathy, demotivation, difficulties in enjoying life, hopelessness, motor inhibition, hypertonia, and negative thoughts, including potentially delusions in cases of severe severity. However, it can also cause a wide range of correlated somatic symptoms, including some organic changes that frequently match up with encapsulated or larval forms of depression [18].

Due to the numerous research studies that have been conducted on the subject and the widespread use that depression has gained in society, it is one of the most well-known psychological concepts. Yet, there are still disagreements regarding the precise definition of depression, as evidenced by the many interchanges between the concepts of emotion, state, illness, and disease. Depression is also sometimes used interchangeably with other terms, such as “melancholy.” Based on the foregoing, the current study aims to analyse the term “depression,” beginning with its definition and producing later reflections on what is discovered in the field [19].

Depression can also be triggered by less serious mental health issues, which are also frequent. More than half of Nigeria's working population suffers from symptoms associated with stress, including anxiety, depression, physical discomfort, social isolation, and sleep disturbances. In addition, Nigeria has just started looking into the relationship between health and work stress in order to create preventative initiatives, especially for those in high-stress occupations like police, fire, and ambulance service. Finding the gene or genes responsible for a problem or making a person more susceptible to it should further our knowledge of the processes in the brain that lead to mental illness and improve diagnostic and treatment options [20].

Depression has been linked to increased rates of morbidity and death, functional impairment, decreased quality of life, and increased use of health services and medical expenses. In the general population, depression is a common psychiatric disease with a lifetime frequency of about 10% [21]. Depression can be persistent or recurrent, significantly affecting a person's capacity to manage everyday life, perform well at work or school, or both.

1. *Types of Depression:* Depression is a critical mental health disorder that is classified as a severe healthcare emergency, as it mostly could not be visibly diagnosed but could portend grave consequences. Some of the major and common depressive episodes include
    - Postpartum depressive disorder,
    - Major depressive disorder,
    - Minor depressive disorder,
    - Bipolar depressive disorder (manic depressive illness)
    - Persistent depressive disorder (dysthymia depressive disorder) and,
    - Seasonal affective depressive disorder.

F. Measuring Severity Levels of Depressive Disorder

The severity of depressive illness is determined by the number and intensity of symptoms, as well as functional disability. We identify the levels as follows:

Mild: Symptoms are those that are distressing but manageable and cause minor impairment in social or occupational functioning but do not exceed those necessary for diagnosis.

Moderate: symptoms, intensity, and functional impairment This condition falls between the categories of "mild" and "severe."

Severe: symptoms exceed the diagnostic threshold, are upsetting and uncontrollable, and significantly impair social functioning.

Severity Level:

- Mild: Two symptoms,
- Moderate: Three symptoms,
- Moderate-severe: Four or five symptoms,
- Severe: Four or five symptoms and motor agitation.

G. Mental Health Challenge in the Workplace

Despite Nigeria’s strategic position in Africa, the healthcare system has suffered several downfalls. Nigeria is greatly underserved in the healthcare sphere due to the fact that health facilities (centres, personnel, and medical equipment) are inadequate in the country, especially in rural areas. While various reforms have been put forward by the Nigerian government to address the wide-ranging issues in the healthcare system, they are yet to be implemented at the state and local government area levels. According to the 2009 communiqué of the Nigerian national health conference, the

healthcare system remains weak as evidenced by a lack of coordination, fragmentation of services, a dearth of resources, including drugs and supplies, inadequate and decaying infrastructure, inequity in resource distribution, and access to care and very deplorable quality of care. The communiqué also highlighted how the various levels of government's unclear roles and responsibilities have exacerbated the situation [22].

The Nigerian healthcare system lacks a robust platform for the provision of electronic health information and patients' record management. This is because the provision of timely information aimed at combating possible health menaces, among many other things, is an important function of public health. Hence, inadequate tracking techniques in the public health sector can lead to huge health insecurity and hence endanger national security, etc. Decades ago, communicable disease outbreaks were a threat not only to the lives of individuals but also to national security. Today it is possible to track outbreaks of diseases and step up medical treatment and preventive measures even before they spread over a large populace.

Mental health is a complex but important workplace issue with numerous ramifications. Historically, organisations have underestimated the impact of mental health issues on their operations. In today's competitive market, organisations must prioritise supporting the mental health of their employees as well as their physical health. It is important for organisations to view mental health promotion as an investment in reducing absenteeism, depression, burnout,stress, poor performance, workplace incidents, poor decision-making, lack of motivation, conflicts, and poor connections with colleagues and customers.

H. Impact of Depression in the Workplace

Major depressive disorder (MDD) has long been recognised as a primary cause of disability worldwide, affecting an estimated 350 million people. Depression frequently begins early and can become chronic or recurring, resulting in significant difficulties in everyday functioning. Recently, there has been increased focus on MDD and other depressive illnesses, with a World Health Assembly calling on the World Health Organisation (WHO) to take action to combat depression and other mental health diseases. This is because, as the world's population grows and ages, the expenses of living with a disability rise. Indeed, the most recent worldwide Burden of Disease 2019 estimates show that the worldwide burden of disease caused by MDD has increased by over 40% in the last two decades. Even in Sub-Saharan Africa, where many communicable diseases remain prominent drivers of disease burden in contrast to the worldwide shift to non-communicable diseases, neuropsychiatric disorders account for approximately 10% of the total disease burden.

Depression is expected to cost the US between $35 million and $50 million annually due to lost productivity. Depressed employees are less productive, have difficulty concentrating, retire earlier, and are more likely to miss work than their non-depressed counterparts. Work takes concentration and regular contact with others, which can be exhausting for those prone to depression. This is especially noticeable in vocations like waiters, medical professionals, and large-scale factory workers. Depression and its treatment have the potential to modify occupational outcomes of functionality, productivity, absenteeism, presenteeism, return to work, work engagement, and unemployment, among others. Psychological screening for depression in the workplace has the potential to identify workers with depression symptoms in varying degrees of severity.

I. Computer Technologies in Healthcare

Numerous facets of our lives have been profoundly impacted by technology. The healthcare industry is one such area that has greatly profited from computer applications in a number of ways. The healthcare business relies significantly on computer tools to deliver high-quality care. For example, disease diagnosis frequently uses software that matches a patient's symptoms to a database of known diseases. This allows medical experts to promptly and properly identify the condition. Similarly, image analysis is a valuable tool for disease diagnosis and therapy. Computer software can detect problems in X-rays, 3D models, and MRI images. Medical practitioners then utilise this information to determine the most effective course of treatment for the patient [23].

The application of computer technologies is basically in the areas of patients' information management, hospital resource management, administration, and disease prediction and diagnosis. With respect to the health information management system, the computers have been deployed to manage patients records and improve healthcare delivery, as patients' information systems that were primarily stored in paper files have now been transformed into digital form, where patients' records are stored in large databases that can be accessed remotely by medical practitioners and physicians from anywhere in the world. This has greatly reduced consultation and waiting time as some healthcare organisations have improved their operations to enable patients to book and get a doctor's appointment remotely.

J. Computer Technologies for Disease Diagnosis

Diseases are abnormal conditions that adversely impact the body and mostly a part of an organ with an external cause of some form of external injury. In medicine, diseases are categorised as mild, severe, acute, infectious, hereditary, and chronic. Chronic or protracted diseases generally last for a longer period, ranging from three months or more in human organs. Chronic diseases may not be prevented using vaccines or cured by medications, which makes early detection of these diseases the best bet for human lives. In the traditional medical diagnosis method, patients encounter a number of challenges due to the rise in health-related issues and the world's population growth, particularly in developing nations such as Nigeria. This situation can result in improper care being given to a patient, which could even result in more health damages and fatalities [24].

In order to address this issue of acute and chronic diseases, technology offers an alternative to the traditional system. As such, it plays a major role in healthcare systems by incorporating a large number of computer-aided supporting systems and tools. This bonding has not only improved patient care but also decreased treatment costs by promoting efficient allocation of medical resources and reducing the

mortality rate. Medical professionals, hardware, and software are the three primary components of technology-enabled healthcare systems. However, creating an autonomous system that can forecast disease using electronically available medical data is extremely difficult. The enormous social effect of this study subject inspires researchers from a variety of disciplines, including computer science, biology and medicine, statistics, and medication design. These researchers are constantly striving to create a near-perfect system for improving patient care.

K. Artificial Intelligence in Healthcare

The broad definition of artificial intelligence is the programming of machines to mimic human performance in tasks. In this field, robots are trained to solve problems in a way that resembles human thought. Planning, perception, learning, and decision-making are all simulated by artificial intelligence. Artificial intelligence devices are designed to sense their environment and respond appropriately, which enhances their performance over time. Artificial intelligence is mostly used in computer vision, natural language processing, human-computer interface, and human-agent interaction, among other closely related subfields. Biomedicine, the environment, education, social sciences, finance and economics, cybersecurity, the automobile industry, government, law, and, most significantly, healthcare have all benefitted greatly from the extensive use of these fields in improving their respective fields.

L. Expert Systems in Healthcare

Medical diagnosis identifies the underlying cause of symptoms and indicators. This result is critical for a person to receive an early warning and treat the disease. Healthcare professionals can assist in medical diagnosis. Medical diagnoses are often performed by human specialists in healthcare facilities. Some individuals may struggle to seek medical diagnosis due to time constraints, high medical check-up prices, or a personal aversion to regular check-ups. However, monitoring health status is essential for everyone.

Intelligent techniques are being used in computer-based systems to simulate medical diagnoses in the age of information technology and the Internet. The techniques incorporate expert knowledge and norms into a computer system to mimic expert decision-making based on supplied information. This intelligent, knowledge-based system, available over the internet, enables self-diagnosis and convenience for individuals. This intelligent, knowledge-based system structure preserves human expert knowledge in a computer system. Self-diagnosis is a crucial aspect of self-care for maintaining good health. It generates good emotions, which boost confidence and self-esteem. Self-care is crucial for individuals and communities, encompassing many actions such as self-monitoring for disease symptoms and identifying the underlying cause.

Medical expert systems (MESs) are commonly used in clinical laboratories, educational settings, clinical monitoring, and data-rich regions such as intensive care units. Intelligent programs can provide tremendous benefits when properly implemented and governed. A computer-based expert system combines facts and heuristics to solve complex decision-making problems using expert knowledge. Expert knowledge plays a crucial role in expert systems. Expert knowledge is derived from multiple sources, including rules of thumb and documented sources, to create a problem-specific knowledge base.

An expert system functions as an interactive system that replies to queries. This includes clarifying and recommending tasks to improve decision-making. Accurate information is vital for developing expert systems. Expert knowledge should be organised in a clear framework that separates data, knowledge, and control. To ensure optimal performance, the expert system is modularly developed. Expert system strategies rely heavily on internal knowledge bases and reasoning capabilities. Expert system development consists of various steps, including problem identification, knowledge acquisition, knowledge representation, application development, testing, and evaluation. Additionally, it demonstrates the ability to reason with uncertainty and provides explanations of reasoning supported by an inference engine.

This technique is based on expert reasoning and is encoded in a computerised system. The knowledge base can be updated and expanded. However, this is challenging due to limited access to specialists, practitioners, and healthcare facilities. This diagnosis system provides flexible and easy access via the internet, making it ideal for today's hectic environment. The adoption of physician-assisted computer systems may help to alleviate severe medical issues. To this end, an expert system could be built to help diagnose inherited disorders. Figure 2.1 shows the basic architecture of an expert system.

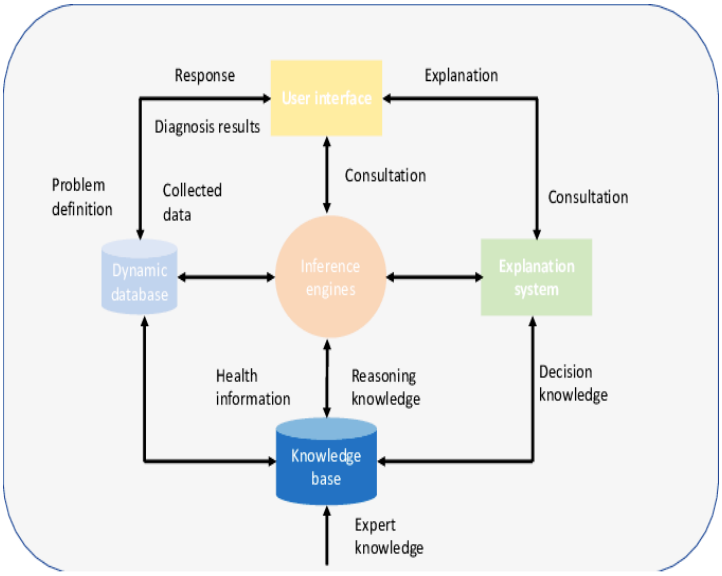

Fig. 1. Architecture of a Clinical Expert System

M. Mobile Healthcare Applications

Mobile healthcare applications have attracted a lot of attention from developers in the software industry with the need for healthcare tools on the go, which has reinforced the proliferation of the mobile application development ecosystem with an emphasis on the development of mobile healthcare (mHealth) tools. Mobile health apps provide easy access to a variety of health-related information. Thirty-one percent (31%) of mobile phone users use their devices to read health-related news, and 20% of smartphone users have at least one health app downloaded and activated [25]. In recent years, there has also been an increase in the usage of wearable devices that collect health data from patients. The data is subsequently sent to a computer application for analysis. This data can be utilised to uncover trends and predict a patient's health. Using mobile computer applications in the healthcare sector is critical to providing high-quality care [23].

According to, an estimated over three billion of the global population own and use a smartphone as of the year 2020, and this is expected to grow by several hundred million years to come. Earlier on in 2015, approximately half a billion smartphone users downloaded at least one healthcare app, and by 2018, fifty percent (50%) of the estimated 3.4 billion mobile technology users will download mobile healthcare (mHealth apps) applications, with fitness apps accounting for 36% of such downloads. The market for mobile healthcare (mHealth) applications is nearing dominance. In an already crowded market, developers and vendors are finding it difficult to obtain viable results.

Usability is one of the major criteria for evaluating mobile healthcare (mHealth) applications, and evaluating the usability of mobile applications will assist designers in quickly detecting usability issues and producing better design solutions. At the creation stage, there is a greater need to pay attention to a product's usability. A common issue with these apps is a lack of appropriate usability evaluation, as research data on the usability of mHealth apps is scarce, and approximately 95% of mobile app usability has yet to be evaluated. The usability construct has been recognised as an important factor for users and developers of any information system.

Similarly, a systematic review of the implementation of mHealth projects in Africa found that interventions provided in this manner had favourable health-related outcomes, though minimal in the Nigerian context further argues that the popularity and potential for massive use and deployment of the mobile healthcare (mHealth) applications in Nigeria have been impeded as the people would prefer to download other business and financial mobile applications more often. This also can be attributed to the rate of downloads of some the these mHealth app which ranges from between ten thousand to fifty thousand downloads annually whiles the fianacial apps have massive downloads of over twenty million per annum.

N. Related Works

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III. METHODOLOGY

The methodology deployed in the development of the workplace depression detection system is the Object-Orientated Analysis and Design (OOAD), which is a software engineering technique that brings together two closely related but independent processes: Object-Orientated Analysis (OOA) and Object-Orientated Design (OOD). It is founded on the ideas of object-orientated programming (OOP) and serves as a systematic and structured method to develop and build software systems [27]. This methodology applies object modelling for the investigation and analysis of the system requirements specification for an organisation or business to proffer the most suitable software solution to meet their needs. Key justifications for the use of the methodology are that it encourages and enhances code reusability, is easy to maintain, is scalable, and is very flexible. Furthermore, the system adopted the use of a mobile application framework for the development of the expert system for depression detection in the workplace using the Android Studio integrated development environment (IDE) with the Java programming language and SQLite database, respectively.

A. Architecture of the Proposed System

The proposed system in Figure 2 shows the different components of the system with the additional mobile application framework that enables it to be deployed on mobile devices and encourages remote usage, especially in the work environment.

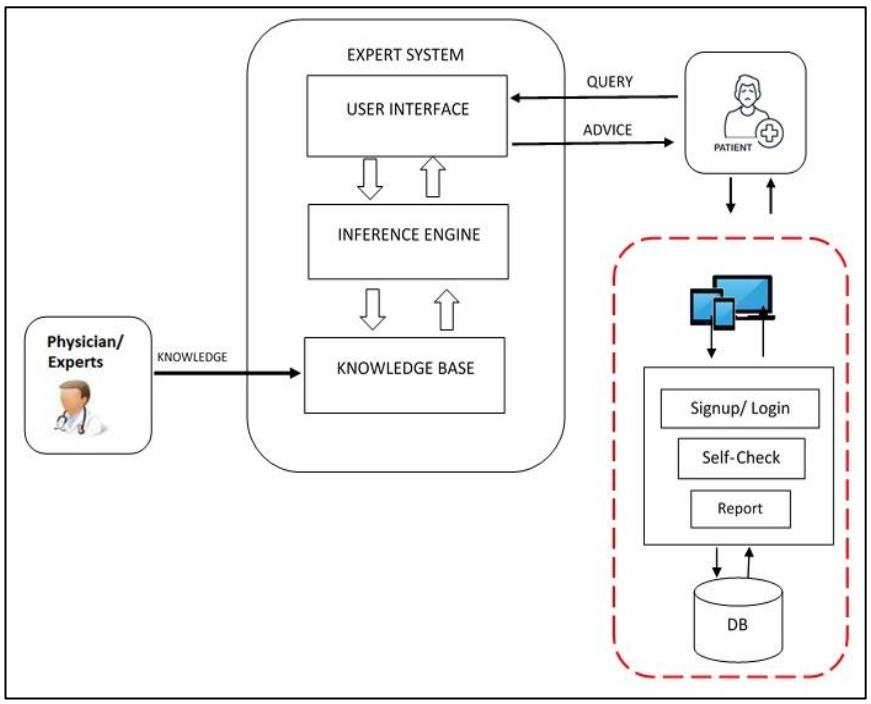

Fig. 2. Proposed Workplace Depression Detection System

The proposed system comprises the signup/login and registration module, the depression self-check and analysis module, a database, and the reporting module, respectively. Once the user has downloaded the mobile depression detection application, the next step is to sign up and register to use it. Once the registration process is done, the user will have to enter some demographic information to build up their profile, and the data would require regular updates as the occasion demands. Once this is done, the user can now access and use the depression self-check and analysis module, which will enable them to self-test their status; a report will be generated on the type and severity of the depression, if any, and the possible remedy before consulting a physician. The system functions in the form of a questionnaire that will require the user to click and check various options that border on the symptoms they are experiencing, and the system will automatically match the symptoms to the type of depression, indicating the severity based on the response from the user on the mobile application.

IV. RESULTS AND DISCUSSION

A Confusion Matrix, an accuracy, precision, F1 score, recall, Mean Absolute Error, Mean Squared Error, and Root Mean Squared Error were used to rate the performance of each model. One hundred and thirteen (112) test cases were used to evaluate each model. We present the obtained set of values as follows.

Each row corresponds to **the actual class**, and each column corresponds to the **predicted class**. The diagonal elements represent the **True Positives (TP)** for each class, while the off-diagonal elements represent the errors distributed as **False Positives (FP)** or **False Negatives (FN).**

For a particular class, I:

- TP: Element [*i*] [*i*] (on the diagonal).
- FP: Sum of elements in column *i*, excluding.
- FN: Sum of elements in row *i*, excluding.
- TN: Sum of all elements excluding row *i* and column *i*.

A. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Table 1: ANFIS Confusion Matrix

Predicted	Class 0 (TP)	Class 1 (FP)	Class 3 (FP)	Class 4 (FP)	Total
Actual Class 0 (TP)	30	0	10	0	40
Actual Class 1 (FN)	20	14	11	0	45
Actual Class 2 (FN)	17	0	34	0	51
Actual Class 0 (FN)	25	0	28	23	76
Total	92	14	83	23	212

Table 2: ANFIS Model Sensitivity and Specificity

Class	Sensitivity	Specificity
No Depression	0.5143	0.8953
Mild	0.7368	0.9438
Moderate	0.48	0.7848
Severe	0.6190	0.8556

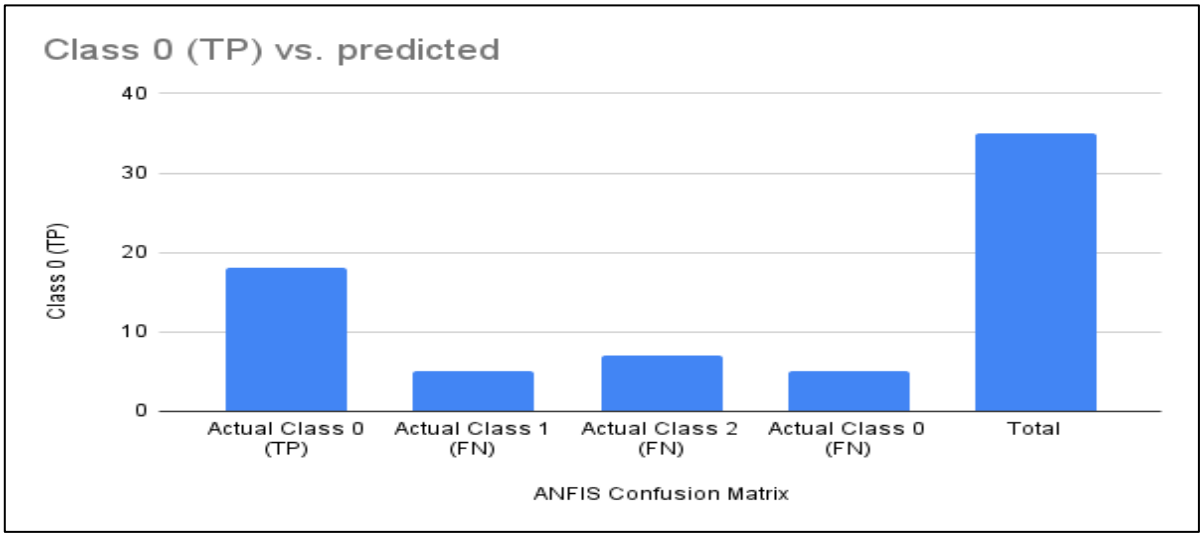

Fig. 3. ANFIS Confusion Matrix

B. Light Gradient Boost Machine (Lgbm)

Table 3. LGBM Confusion Matrix

Predicted	Class 0 (TP)	Class 1 (FP)	Class 3 (FP)	Class 4 (FP)	Total
Actual Class 0 (TP)	14	0	13	0	27

Actual Class 1 (FN)	0	14	14	0	28
Actual Class 2 (FN)	2	0	29	0	31
Actual Class 0 (FN)	0	0	13	13	26
Total	16	14	69	13	112

Table 4. ANFIS Model Sensitivity and Specificity

Class	Sensitivity	Specificity
No Depression	0.5143	0.8953
Mild	0.7368	0.9438
Moderate	0.4800	0.7848
Severe	0.6190	0.8556

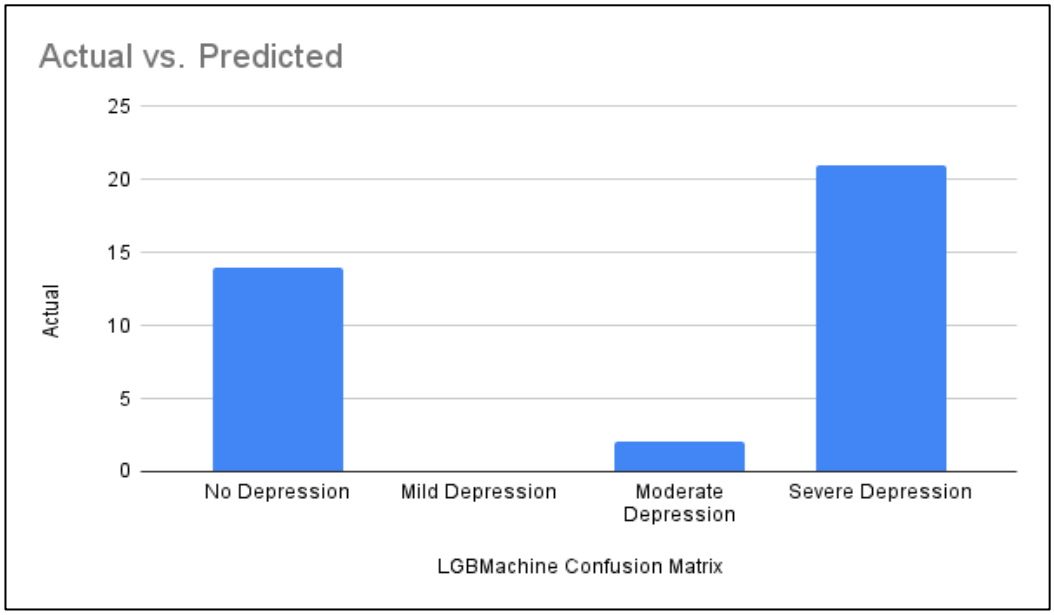

Fig. 4. LGBM Confusion Matrix

C. Logistic Regression (LR)

Table 5. LR Confusion Matrix

Predicted	Class 0 (TP)	Class 1 (FP)	Class 3 (FP)	Class 4 (FP)	Total
Actual Class 0 (TP)	24	14	29	0	67
Actual Class 1 (FN)	0	15	33	0	48
Actual Class 2 (FN)	13	15	13	0	41
Actual Class 0 (FN)	23	15	18	0	56
Total	60	79	93	0	212

Table 6. LR Model Sensitivity and Specificity

Class	Sensitivity	Specificity
No Depression	0.4667	0.8415
Mild	0.2632	0.8701
Moderate	0.3651	0.4805
Severe	0.00	0.000

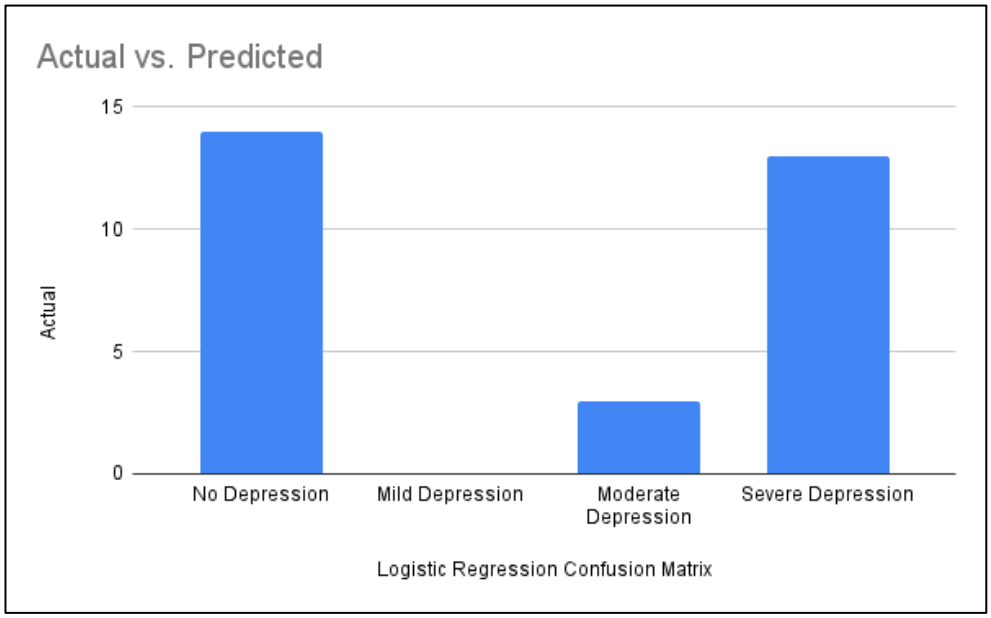

Fig. 5. LR Confusion Matrix

D. Extreme Gradient Boosting (Xgboost)

Table 7. XgBoost Confusion Matrix

Predicted	Class 0 (TP)	Class 1 (FP)	Class 3 (FP)	Class 4 (FP)	Total
Actual Class 0 (TP)	38	0	19	0	57
Actual Class 1 (FN)	25	24	29	0	78
Actual Class 2 (FN)	17	0	34	0	31
Actual Class 0 (FN)	5	0	8	13	26
Total	35	14	50	13	112

Table 8. XgBoost Model Sensitivity and Specificity

Class	Sensitivity	Specificity
No Depression	0.5143	0.9151

Mild	1.0	1.0
Moderate	0.48	0.59
Severe	1.0	1.0

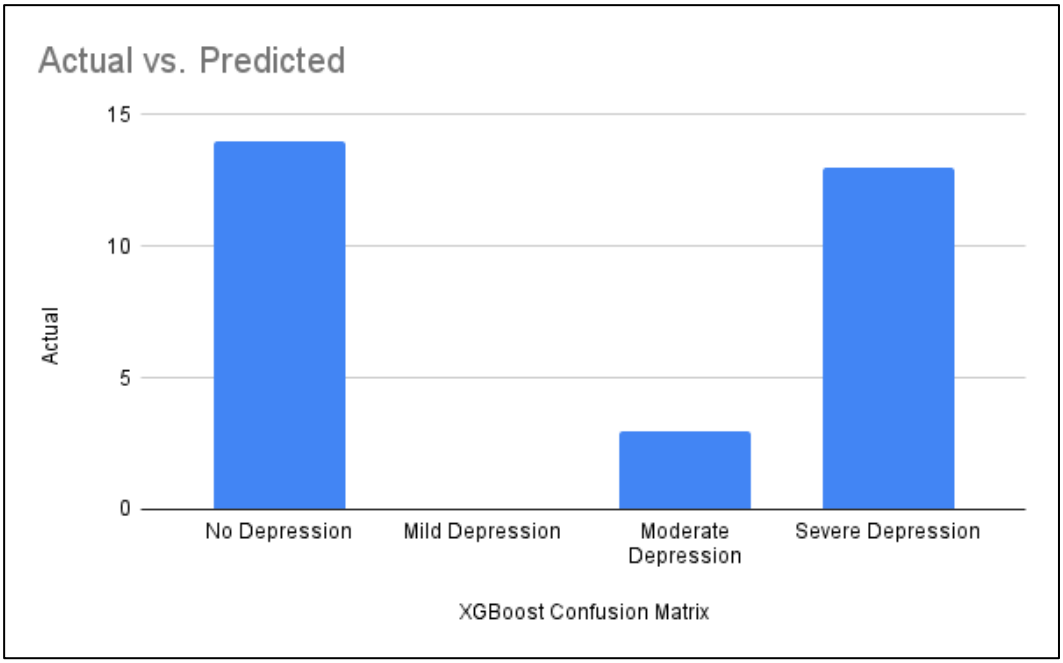

Fig. 6. Xgboost Confusion Matrix

Table 9. Models Comparison

Model	**Accuracy**	**F1 score**	**MAE**	**MSE**	**Precision**	**RMSE**	**Recall**
ANFIS	0.9121	0.9254	0.9121	1.1626	0.9390	1.0825	0.9121
LightGBM	0.625	0.6389	0.5089	0.7768	0.8094	0.8814	0.625
XGBoost	0.6161	0.6254	0.6161	1.1696	0.7390	1.0815	0.6161
Logistic Regression	0.375	0.3071	1.0089	2.0089	0.2793	1.4174	0.375

Table 10. Models Sensitivity and Specificity Comparison

Model	**ANFIS**		**LGBM**		**XGB**		**LR**	
Class	sense	Spec	sens	spec	sense	Spec	sense	spec
No Depression	0.5143	0.8953	0.5143	0.8953	0.4667	0.8415	0.5143	0.9151
Mild	0.7368	0.9438	0.7368	0.9438	0.2632	0.8701	1.0	1.0
Moderate	0.48	0.7848	0.4800	0.7848	0.3651	0.4805	0.48	0.59
Severe	0.6190	0.8556	0.6190	0.8556	0.00	0.000	1.0	1.0

Table 11. Comparison of People with and without Depression

Criteria	People Without Depression	People With Depression
Emotional State	Stable emotions, balanced mental health	Persistent sadness, emotional distress
Interest in Activities	Engaged in hobbies and work activities	Loss of interest in once-enjoyed activities
Work Performance	High productivity, effective task completion	Impaired capacity to perform tasks
Physical Health	Generally healthy, minimal health complaints	Prone to emotional and physical health issues
Job Retention	Stable employment, consistent performance	Higher risk of job loss due to poor performance
Risk of Suicide	Low risk, emotionally resilient	Increased risk of suicide
Impact on Organization	Enhances workplace productivity and efficiency	Causes loss of revenue and reduced efficiency
Need for Intervention	No immediate need for mental health support	Requires early detection and timely intervention
Workplace Behaviour	Engages in teamwork, communicates effectively	Withdrawal from colleagues, lack of motivation
Technology Intervention	Less likely to need workplace mental health apps	Benefits from mobile app-based depression detection

Workplace depression has silently continued to destroy the labour force of nations around the world, resulting in low productivity, low self-esteem, and the possibility of death owing to an inherent suicidal tendency. The symptoms range from decreased appetite and/or weight reduction to increased appetite and weight gain. Loss of interest in previously liked activities, especially sex. This silent killer disease, which causes restlessness, irritation, and other symptoms, is still ravaging the workplace and the mental health of individuals and groups. The findings of this study, as depicted in the application's many functional components, are intended to aid in the early diagnosis, reduction, and treatment of the condition, hence further slowing the mortality rate.

Figure 3 shows the registration and login activity module of the new system which allows the users to download and install and create account/ register to use the system while figure 4 shows the login activity module that allows for user authentication. To ensure data integrity, confidentiality and security, only registered users can access and use the system. This module also serve as the security and access control module of the new workplace depression detection system.

Fig. 7. Registration Module

Fig. 8. Login Form

The process for the detection of the depression in the workplace is carried out when the user have successfully logged in to the system after registering to create account. This is done as indicated in figure 5 which is the depression detection module where the users are allowed to use the check boxes to check the various symptoms available to ascertain their status. Here also the user will be prompted to check each box with respect to the symptoms and feeling they observed within themselves and when they are done, they click on the "Evaluate" button to ascertain their depression status with a feedback report on the same screen as indicated in RED. After the evaluating their status based on the report from the check symptoms, the user can further assess the severity of the disease by clicking the "Check Severity" button which eventually moves to figure 6 which is the symptom severity check activity module. At the Symptoms severity check module, the user can now assess the severity of the disease by clicking the drop down combo box to select the level of occurrence of the symptoms which is used to determine the severity of the disease as indicate in figure 6.

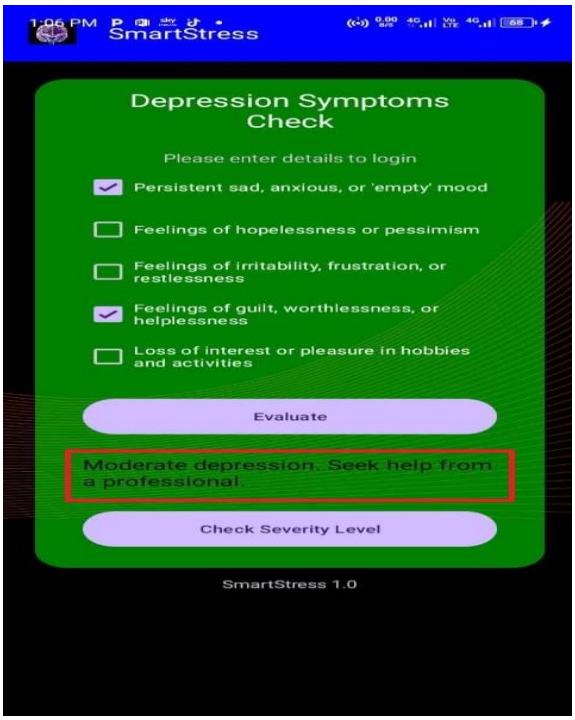

Fig. 9. Depression Check Module

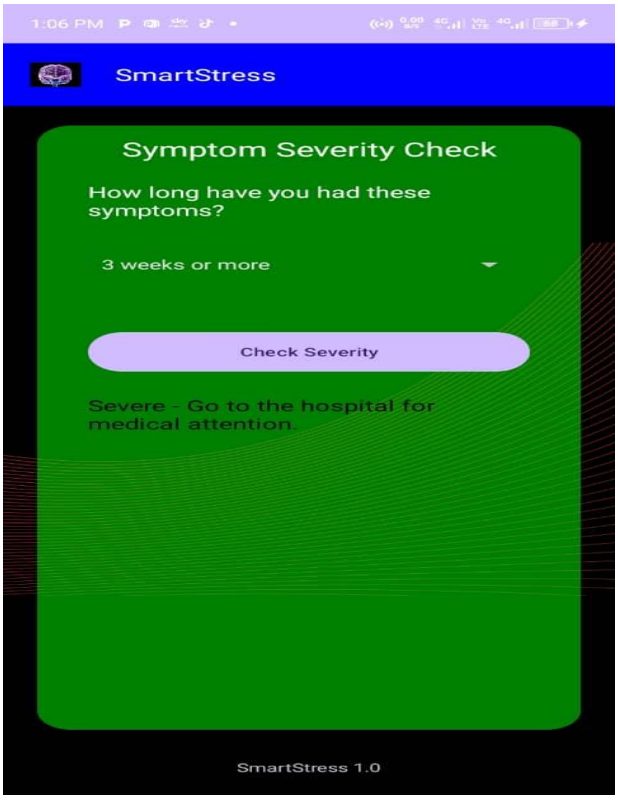

Fig. 10. Severity Check

E. System Evaluation

Therefore, the new system which is mobile application promotes patient-centered care and reduces the risk of workplace depression with the self-assessment/ check mobile application for early and detection of depression to enhance the mitigation and treatment of the disease. Table 1 shows the comparative review of the existing systems and the new depression detection system.

Table 12. Comparative Review of Existing and Proposed System

S/N	Evaluation Criterion	Existing System	New/ Proposed System
1	Process time	60 seconds	10 seconds
2	Process mode	Online only	Online and offline.
3	Access mode	Doctors only	Patient-centered
5	User Experience	None	High and impressive
6	Accuracy of results	65%	90%
7	Security	Unknown	High
8	Portability and accessibility	Low	High
9	Assessment module	Multiple module	Single module

The new system, as shown in Table 1, outperformed the existing system in several areas with respect to process time, access mode, user experience (UX), security, and portability. The proposed system is patient-centered, which makes it user-friendly, as the patient has the liberty to check and assess their depression status on the go and in the workplace, enabling them to make a quick decision to see the physician before it's too late. One key takeaway of the new system is that it provides an avenue for early detection of the disease, thereby mitigating the possible mental health collapse and reducing the mortality rate. The new system, therefore, is efficient, user-friendly, secure, and portable and can be used both online and offline.

F. Policy Implications

Implementing a **system for detecting workplace depression over time** with **objective measures** has several **policy implications** at organisational, governmental, and public health levels. These implications can shape workplace

policies, mental health regulations, and employee welfare initiatives.

1. *Workplace Policies & Mental Health Regulations*
   a) *Mandatory mental health screenings in workplaces*
      - Employers might need to do regular checks on their employees' mental health using objective tools like clinician-rated scales (HAM-D, MADRS), physiological tracking, and AI-based emotional analysis.
      - Companies could integrate depression screenings into annual health checkups to ensure early intervention.

   b) *Workplace Mental Health Support Systems*
      - Organisations may need to expand their employee assistance programs (EAPs) by incorporating mental health professionals, AI-driven screening tools, and remote therapy options.
      - The findings suggest that early detection and intervention can improve employee productivity, which encourages HR policies to prioritise mental health support.

   c) *Confidentiality and employee rights*
      - Policies must balance workplace monitoring with employee privacy by implementing data protection protocols (e.g., GDPR-compliant AI models).
      - Develop opt-in systems to prevent forced participation and potential discrimination among employees.
      - Anti-discrimination laws should be strengthened to protect employees diagnosed with depression from unfair treatment.

2. *Government and Public Health Policy Implications*
   a) *Integration of AI in National Mental Health Strategies*
      - Governments could adopt AI-driven mental health screening tools into public healthcare systems.
      - National health departments may consider funding research & development for AI-based depression detection in workplaces.

   b) *Mental Health Coverage in Insurance Policies*
      - Insurance policies should cover AI-assisted mental health screenings and interventions, reducing the financial burden on employees seeking treatment.
      - Employers may be incentivised (via tax breaks or subsidies) to provide mental health resources to employees.

   c) *Workplace depression is a recognised occupational health issue.*
      - The study highlights the impact of depression on productivity, supporting policy changes that classify workplace depression as an occupational health risk.
      - Governments could mandate mentally healthy work environments, requiring organisations to adopt preventive measures.

3. *Ethical and Legal Considerations*
   a) *AI Ethics & Bias Prevention*
      - Policies should ensure AI models used in depression detection are unbiased, validated across diverse populations, and free from racial, gender, or socioeconomic bias.
      - Employers must not use depression scores for discriminatory practices, such as denying promotions or terminating employees.

   b) *Data Security & Privacy Laws*
      - Policymakers must establish clear data governance rules to ensure that biometric, behavioural, and mental health data collected via AI is secure and not misused.
      - Organisations should be required to anonymise employee data and seek informed consent before collecting mental health-related metrics.

4. *Economic Implications and Workforce Productivity*
   a) *Cost-Benefit Analysis for Employers*
      - The system's findings indicate that early depression detection reduces absenteeism and improves productivity, justifying corporate investments in mental health AI systems.
      - Companies that invest in mental health AI platforms may experience higher workforce efficiency and lower healthcare costs due to fewer burnout cases.

   b) *National Productivity & Economic Growth*
      - Depression-related productivity loss costs billions annually; policies promoting early intervention can help boost workforce efficiency and national economic growth.
      - Policymakers may consider grants or incentives for businesses that integrate mental health AI solutions to enhance employee well-being.

V. CONCLUSIONS

The goal of this study was to lower the risk and death rate of workplace depression by creating a mobile app that would allow users to self-evaluate their own risk of the disease. This would also make the workforce more effective and efficient because workers would be able to detect the disease using their phones instead of taking time off to go to healthcare facilities and doctors' offices, which would waste valuable work hours and could lead to death from the disease. We developed this paper using the Java programming language in the Android Studio IDE. This application can help users easily assess their depression status and severity remotely from anywhere and get their health report immediately. This application is very useful in maintaining better health for the population; it is very portable and flexible with a friendly interface that simplifies usage.

The system shows promise in identifying depression and improving workplace productivity, but its effectiveness may vary when applied to different populations or work environments. The system's foundation in Android Studio with Java and Kotlin makes it portable across Android devices, which is an advantage in terms of accessibility. However, its implementation may be limited if the target

workforce predominantly uses other platforms, such as iOS or web-based applications. To properly evaluate the system's usefulness across different job roles, industries, and geographical areas, its user base must also be diverse. Workplaces in high-tech sectors might see quicker adoption, while industries with lower technological penetration could face barriers in integrating such a system. Additionally, organisations with strong mental health support systems might benefit more from the system's proactive interventions, whereas those with limited awareness of mental health issues might struggle to effectively implement them.

The cultural context is another critical factor. In regions or industries where mental health is stigmatised, employees may be less willing to engage with the system, potentially skewing the results. The work culture, particularly in high-stress environments where depression manifests differently, could influence the effectiveness of the system. Consequently, the system would need to be tailored to account for these cultural nuances, ensuring that it respects privacy and addresses unique mental health challenges within different organisational frameworks.

Furthermore, because the system is designed to detect depression through behavioural and physiological data, it must be tested across diverse demographics to ensure it does not exhibit bias. The tool's generalisability will depend on its ability to adapt to a wide range of socio-economic groups, ensuring its accuracy in detecting depression across different ages, genders, and cultural backgrounds.

The system has the potential for enhancing productivity and providing early intervention; its scalability and long-term effectiveness can only be determined through broader and more varied implementations. A multi-organizational study would be essential to assess how the system performs in both large- and small-scale environments, adjusting for organisational differences and employee needs. Thus, while the system holds significant promise, its broader application requires careful testing and adaptation to diverse environments to ensure it remains effective and accessible to all.

RECOMMENDATION

This paper is meant to simplify the process of delivering basic mental healthcare services with respect to the detection and mitigation of cases of workplace depression. Therefore, we recommend this work to the following groups and individuals:

i. Businesses and organizations with small, medium and large workforce,
ii. Doctors and medical practitioners could adopt and use the application, as it was designed to suit their needs with an easy-to-use interface.face,
iii. Patients and users can use it for self-assessment of their depression status to reduce the risk of disease,
iv. Government and NGOs involved in mental healadvocacy, especially major depressive disorders, for the prevention and treatment. They can also leverage the application to improve their advocacy to mitigate and reduce the risk of the disease.

SUGGESTION FOR FUTURE WORKS

This new system developed in the study is an expert system for depression detection using a a mobile application development framework, which makes it portable and easy to use without directly visiting the hospital. This work can be further improved with the integration of artificial intelligence and the Internet of Things through the development of wearable applications and devices for the detection of mental health disorders, taking depression as a case study.

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