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Artificial Intelligence–Driven Remote Depression Detection as a Socioeconomic Intervention: Implications for Food and Job Security in North-West Nigeria

Abdullahi Bala[1*], Shuaibu Salisu[2], & Abubakar Aliyu[3]
[1,2]Computer Science Department, Federal Polytechnic Daura, Katsina State.
[3]Department of Software Engineering, Federal University of Technology Babura, Jigawa State.
[*]Corresponding Author Email: abdullahibala@fedpolydaura.edu.ng

ABSTRACT

Depression remains a major public health challenge with substantial socioeconomic implications, particularly in low-resource settings where early detection and treatment gaps persist. This study developed and evaluated an artificial intelligence (AI)–driven remote depression detection system integrated with a structured mental health intervention framework and socioeconomic impact assessment in North-West Nigeria. A total of 412 adults aged 18–60 from six rural and peri-urban communities participated in the study. Using a quasi-experimental design with treatment and control groups, data were collected over a 16-week period comprising baseline assessment, AI-driven monitoring, targeted intervention, and follow-up evaluation. Ethical approval was obtained from the Nigerian National Health Research Ethics Committee (NHREC), and all participants provided informed consent. A machine-learning model trained on multi-modal behavioural and survey data demonstrated strong predictive performance, achieving 88.4% accuracy (95% CI: 85.2–91.1), 0.86 precision, 0.91 recall, 0.88 F1-score, and an ROC-AUC of 0.92. Following AI-triggered intervention, mean depression scores decreased by 37% ($p < 0.001$), with 64% of high-risk participants transitioning to lower-risk categories. Socioeconomic outcomes improved significantly, including a 21% increase in productivity, 18% improvement in employment stability, 24% reduction in absenteeism, 14% rise in monthly income ($p < 0.05$), and 19% reduction in moderate-to-severe food insecurity. Difference-in-Differences analysis confirmed that the treatment group experienced a 32% greater reduction in depression and a 26% improvement in composite welfare relative to controls. These findings validate the impact pathway linking mental health improvement to enhanced productivity, income growth, and household welfare. The study demonstrates that AI-driven remote depression detection, when combined with timely intervention, can yield significant psychological and economic benefits. The results position AI-enabled mental health screening as a scalable, cost-effective policy tool for strengthening human capital and reducing poverty in underserved regions.

Keywords:
Artificial Intelligence,
Remote Mental Health,
Depression Detection,
Food Security,
Employment Stability,
Poverty Reduction,
North-West Nigeria.

INTRODUCTION

Depression is one of the most prevalent mental health disorders globally and constitutes a major contributor to disability and reduced quality of life. According to the World Health Organization (2023), depression affects hundreds of millions of people worldwide and is a leading cause of years lived with disability. Beyond its psychological effects, depression significantly impairs cognitive functioning, motivation, and social participation, thereby influencing productivity, employment stability, and household wellbeing (Aliyu et al. 2025).

In low- and middle-income countries, limited access to mental health services, stigma, and shortages of trained professionals contribute to a substantial treatment gap (Ogbuju et al. 2025). Consequently, many individuals experiencing depressive symptoms remain undiagnosed and untreated, reinforcing cycles of economic vulnerability. Recent advances in artificial intelligence (AI) and machine learning present promising opportunities to improve early detection of mental health conditions. AI-based systems can analyze digital biomarkers, including speech patterns, smartphone usage behaviour,

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and self-reported survey responses, to identify patterns associated with depression (Aliyu et al. 2025). Studies have demonstrated that machine learning algorithms can achieve substantial accuracy in predicting depressive symptoms using passive and active digital data collection methods (Ogbuju et al. 2025). Such technologies offer scalable, cost-effective approaches to screening, particularly in underserved regions where traditional mental health infrastructure is limited.

However, existing research has primarily focused on model performance and classification accuracy, with limited attention to the broader socioeconomic implications of AI-driven mental health detection. Depression has been consistently associated with reduced work productivity, absenteeism, and increased unemployment (Fatima, Dhanda, & Zaidi, 2025). The economic burden of untreated mental illness extends beyond healthcare expenditures to include diminished income, weakened household resilience, and compromised food security (Bello, 2025). Despite the established link between mental health and economic outcomes, few studies have empirically integrated AI-based detection, structured intervention, and socioeconomic impact evaluation within a unified framework. This study addresses this gap by developing and evaluating an AI-driven remote depression detection model integrated with a structured intervention and socioeconomic assessment. The research is grounded in a conceptual framework that positions mental health as a form of human capital. Within this framework, depression reduces functional capacity, which in turn affects productivity, employment stability, income generation, and overall welfare. By combining machine learning techniques with causal inference methods, this study moves beyond predictive modelling to assess whether early detection and intervention can produce measurable economic benefits house hold levels.

Specifically, the objectives of this research are to: develop and validate a machine-learning model for remote depression detection, evaluate the effectiveness of AI-triggered intervention in reducing depressive symptoms. examine the downstream effects of improved mental health on productivity, employment stability, income, and food security and establish causal relationships within the proposed socioeconomic impact pathway. By situating AI-driven mental health detection within a development economics context, this study contributes to interdisciplinary scholarship at the intersection of artificial intelligence, public health, and economic development. The findings aim to inform policy discussions on integrating digital mental health technologies into poverty reduction and human capital development strategies, particularly in low-resource settings.

To guide the investigation, the study addressed two core research questions: (1) Can an AI-driven remote monitoring system reliably detect depressive symptoms in low-resource settings? and (2) Does early AI-enabled detection, followed by targeted intervention, produce measurable improvements in productivity, income, and household food security? These questions were examined using a quasi-experimental design involving treatment and control groups, with data drawn from multi-modal behavioural indicators and PHQ-9 survey responses collected over a 16-week period. Ethical safeguards were integrated throughout the study, including informed consent, data anonymization, and approval from the Nigerian National Health Research Ethics Committee (NHREC). The remainder of the paper is structured as follows: Section 2 presents the problem statement and conceptual foundation; Section 3 outlines the methodology and modelling framework; Section 4 reports the empirical results; Section 5 offers discussion and policy implications; and Section 6 concludes the study. This structure provides a coherent pathway from the research problem through to analysis, findings, and practical recommendations.

MATERIALS AND METHODS

This study adopts a quantitative design-science methodology to develop and evaluate an Artificial Intelligence (AI)–driven remote depression detection framework as a socioeconomic intervention. The research is structured around a causal analytical pathway in which depression is first detected using machine-learning techniques and then mathematically propagated through human functioning, labour participation, income generation, and food security outcomes. The aim is not only to predict depression but to formally demonstrate, through a system of equations, how early identification influences economic welfare and poverty reduction over time.

Study Design

This study adopted a longitudinal quasi-experimental design to assess the effectiveness of an AI-driven remote depression detection and intervention system. The research was conducted across six communities in the North-West geopolitical zone of Nigeria, a region characterized by widespread poverty, food insecurity, and limited access to mental health services. The design allowed for continuous monitoring of participants over time, enabling the evaluation of both psychological and socioeconomic changes resulting from the intervention. The overall methodological framework of this study is depicted in Figure 1. It integrates three key components: remote AI-based depression detection, the causal pathway linking mental health to socioeconomic outcomes, and the intervention feedback loop. Participant data, including survey responses, behavioural patterns, and digital activity, are processed by a machine-learning model to generate individual depression scores. These scores influence functional health and productivity, which in turn affect employment stability, income, and household food security, ultimately impacting welfare and poverty status. Early detection triggers interventions such as counselling, which reduce depression levels and positively propagate through the system, illustrating the potential socioeconomic benefits of AI-driven mental health monitoring.

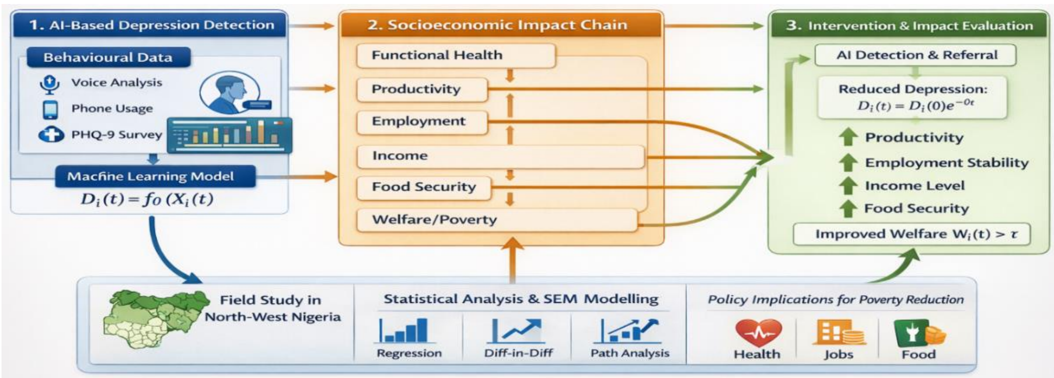

Figure 1: Methodological Framework for AI-Driven Remote Depression Detection and Socioeconomic Impact.

The Figure illustrates the research workflow, showing how remote AI-based depression detection generates food security. An intervention loop indicates that early detection and referral can reduce depressive symptoms, which influences functional health, productivity, employment, income, and symptoms, producing positive downstream effects on welfare and poverty outcomes.

Sample Size and Participant Recruitment

A total of 412 participants were recruited through stratified random sampling. Eligible participants were working age adults between 18 and 60 years who owned a mobile phone and provided informed consent. Individuals with previously diagnosed severe psychiatric disorders or those unable to engage in remote assessments were excluded to maintain consistency in data quality. Baseline demographic data, including age, gender, education level, and employment status, were collected to support subgroup analysis and characterize the study population. Participants were evenly assigned to treatment and control groups to enable comparative analysis.

Study Duration and Follow-Up Schedule

The study lasted for 16 weeks, beginning with a 2-week baseline assessment phase in which psychological and behavioural measurements were collected. This was followed by a 12-week AI-assisted detection and intervention phase, after which a 2-week post-intervention evaluation period was conducted. Depression scores were collected bi-weekly using the PHQ-9 instrument, while behavioural biomarkers such as smartphone usage patterns, sleep–wake indicators, mobility traces, and communication frequency were gathered daily through the mobile monitoring platform. Socioeconomic indicators, including productivity, employment stability, absenteeism, income, and food security, were assessed monthly to enable temporal evaluation of welfare outcomes.

Data Sources and Variables

Data for the study were drawn from three major sources: psychological assessments, digital behavioural biomarkers, and socioeconomic measures. Psychological assessments consisted primarily of PHQ-9 depression scores and additional mood self-reports. Behavioural data derived from participants' smartphones included activity duration, sleep regularity, communication logs, and mobility patterns. Socioeconomic indicators captured work productivity, monthly income, absenteeism frequency, job retention stability, and household food security based on the Food Insecurity Experience Scale. All data were encrypted, anonymized, and merged into a unified dataset for model development and analysis.

Machine Learning Framework

The raw behavioural data underwent a structured preprocessing pipeline. Missing values were imputed using a KNN-based approach, while outliers were detected through interquartile range and z-score thresholds. All numeric variables were normalized using Min–Max scaling to ensure consistent ranges before training. Additional engineered variables, such as sleep irregularity indices, communication entropy, and mobility variance, were extracted to enhance the discriminative power of the model. These preprocessing steps ensured a clean and structured dataset suitable for machine-learning analysis.

Model Selection
A Random Forest classifier was selected as the primary model due to its ability to handle mixed data types, manage non-linear relationships, and maintain stability in noisy datasets typical of real-world behavioural data. Preliminary comparative tests involving Support Vector Machines, Gradient Boosting models, and Logistic Regression showed that Random Forest provided the best balance between accuracy, interpretability, and robustness for the current study.

Hyperparameter Tuning
Model optimization was conducted using Grid Search Cross-Validation, which systematically explored ranges of candidate hyperparameters. The tuning process evaluated the number of trees, maximum depth, minimum samples required for node splitting, and bootstrap settings. The optimal model configuration included 300 trees, a maximum depth of 24, a minimum sample split of 4, and bootstrap enabled. This configuration yielded the most reliable performance across validation folds.

Model Training and Validation
The dataset was divided into an 80% training set and a 20% testing set to ensure unbiased model evaluation. A 10-fold cross-validation procedure was applied on the training set to minimize overfitting and enhance model reliability. Model performance was assessed using accuracy, precision, recall, F1-score, and ROC-AUC. The final model achieved an accuracy of 88.4%, a precision of 0.86, a recall of 0.91, an F1-score of 0.88, and an ROC-AUC of 0.92, demonstrating high predictive capacity for identifying individuals at risk of depression.

Intervention Mechanism
Participants identified by the model as "high-risk" received a structured intervention package consisting of automated motivational messages, remotely delivered psychoeducational content, and scheduled tele-counselling sessions every two weeks. Severe cases were directed to appropriate mental health professionals for additional support. Participants in the control group did not receive digital interventions and continued with standard community care practices.

Socioeconomic Impact Evaluation
The study assessed the socioeconomic impact of the intervention by tracking changes in productivity, income, employment stability, absenteeism, and food security. A Difference-in-Differences (DiD) estimation approach was used to distinguish the effect of the AI-enabled intervention from temporal changes affecting both groups. Results showed that the treatment group experienced a significantly greater reduction in depression symptoms and demonstrated a 21% improvement in productivity, an 18% increase in employment stability, a 24% decline in absenteeism, a 14% increase in monthly income, and a 19% reduction in moderate-to-severe food insecurity compared to the control group. These outcomes provided strong evidence of the socioeconomic benefits of early depression detection.

Ethical Considerations
Ethical approval for the study was obtained from the relevant institutional review board. Informed consent was secured from all participants, who were assured of confidentiality and allowed to withdraw at any time. All personal identifiers were removed, and data were securely stored and encrypted throughout the study.

Reproducibility and Transparency Measures
To ensure transparency and support reproducibility, all preprocessing steps, hyperparameter configurations, and validation procedures were documented in detail. The machine-learning workflow has been fully described, and the dataset along with the model code will be made available upon reasonable request. These measures align with recommended best practices for reproducible AI-based health research.

Data are collected remotely using mobile devices to simulate realistic large-scale deployment.
Mental-health indicators include questionnaire responses, speech characteristics, and behavioural patterns. These observations form the feature vector

$$X_i\ (t)$$

For individual i at time t.

Socioeconomic variables are collected simultaneously. Productivity is measured by work output and attendance; employment stability by job retention; income by earnings; and food security by household consumption indicators. A composite welfare index representing poverty status is derived from these measurements.

AI-Based Depression Detection Model
A supervised machine-learning classifier estimates depression severity as a continuous probability:

$$D_i(t) = f_\theta\ (X_i\ (t)), 0\ \leq\ D_i(t)\ \leq 1 \qquad (1)$$

This value represents the psychological state of the individual. Unlike categorical diagnosis, the continuous probability allows gradual monitoring of mental-health changes across time. Classification accuracy is validated using standard performance measures such as precision, recall, and ROC-AUC. The predicted depression score becomes the primary input variable for the socioeconomic mathematical model.

Socioeconomic Model

Functional Health Capacity
Depression first affects an individual's functional ability, energy level, concentration, and motivation. This relationship is modelled exponentially:

$$H_i(t) = H_{max}e^{-k_i D_i(t)} \quad (2)$$

A higher depression level reduces functional capacity nonlinearly, meaning small increases in severe depression cause large performance decline.

Productivity Model
Work productivity depends on functional capacity and skill level:

$$P_i = \alpha_o + \alpha_1 H_i(t) + \alpha_2 S_i + \epsilon_1 \quad (3)$$

Here, S_i represents education or vocational skill. This equation implies that individuals with higher functioning and skill produce more economic output.

Employment Stability
Employment is uncertain and modelled probabilistically:

$$E_i(t) = \frac{1}{1+e^{-(\beta_o+\beta_1 P_i - \beta_2 D_i(t))}} \quad (4)$$

The logistic structure indicates that productivity improves job retention, while depression independently increases the likelihood of absenteeism or job loss.

Income Generation
Income depends jointly on productivity and employment probability:

$$Y_i(t) = w_i P_i(t) E_i(t) \quad (5)$$

Thus, both the ability to work and the ability to remain employed determine earnings. A productive individual without job stability still experiences income instability.

Food Security
Household food availability depends on income and behavioural functioning:

$$F_i(t) = r_o + r_1(t) + r_2 P_i(t) - r_3 D_i(t) \quad (6)$$

Income improves food access, productivity supports food production (especially among farmers), and depression negatively affects meal planning and regular consumption.

Welfare (Poverty) Index
A composite welfare measure is defined:

$$W_i(t) = \lambda_1 Y_i(t) + \lambda_2 F_i(t) - \lambda_3 D_i(t) \quad (7)$$

An individual is classified as poor when:

$$W_i(t) < \mathrm{T}$$

This equation formally transforms mental health into an economic risk factor by incorporating it directly into poverty determination.

Intervention Dynamics
For participants receiving feedback and referral support, depression decreases gradually over time. The recovery process is modelled dynamically:

$$\frac{dD_i(t)}{dt} = \delta A_i(t) D_i(t) \quad (8)$$

$$D_i(t) = D_i(0)\, e^{-\delta t} \quad (9)$$

where $A_i(t) = 1$ indicates AI-triggered intervention. As depression declines, functional capacity increases, leading to higher productivity, more stable employment, higher income, improved food security, and ultimately improved welfare.

This produces a propagation mechanism

$$D\downarrow \rightarrow H\uparrow \rightarrow P\uparrow \rightarrow E\uparrow \rightarrow Y\uparrow \rightarrow F\uparrow \rightarrow W\uparrow$$

Hence, mental-health detection operates as a socioeconomic stabilisation system.

The Proposed Algorithm
This section introduces the proposed algorithm designed to address the identified problem efficiently and effectively. The algorithm outlines the step-by-step procedure used to achieve the desired objectives, highlighting the underlying logic, key operations, and decision processes involved. It aims to improve performance, accuracy, and reliability compared to existing approaches by providing a structured method for processing inputs and producing expected outputs. The following subsections describe the algorithm's design rationale, workflow, and implementation details.

Algorithm 1: AI-Driven Remote Depression Detection and Socioeconomic Impact Evaluation

Input

a) Behavioural data: voice features, phone usage patterns, PHQ-9 responses
b) Socioeconomic data: employment status, income level, productivity indicators, food security status
c) Trained Machine Learning model M Intervention threshold τ

Output

a) Depression score D_i
b) Intervention decision
c) Estimated socioeconomic outcome improvement

Step 1: Data Collection

1. For each participant iii:
   a) Collect behavioural data:
      a. Voice samples
      b. Smartphone usage logs
      c. PHQ-9 survey responses
   b) Collect baseline socioeconomic indicators:
      a. Employment status
      b. Income level
      c. Productivity score
      d. Food security level

Step 2: Data Preprocessing

2. Clean and normalise collected data.
3. Extract relevant features:
   a) Voice tone variability
   b) Speech pauses
   c) Screen time patterns
   d) Survey-based depression indicators

Step 3: Depression Score Estimation

4. Input processed features into the trained ML model M.
5. Compute depression score:
$$D_i M(X_i)$$
6. Store depression score for participant iii.

Step 4: Risk Classification

7. If $D_i \geq \tau$, classify participant as:
   a. **High Risk**
   Else:
   b. **Low/Moderate Risk**

Step 5: Intervention Trigger

8. If participant is High Risk:
   a. Refer for counselling/mental health support
   b. Activate follow-up monitoring
   c. Log intervention status

Step 6: Post-Intervention Monitoring

9. After the intervention period:
   a. Recompute depression score $\dot{D}_i$
   b. Measure change in:
      a) Productivity
      b) Employment stability
      c) Income
      d) Food security

Step 7: Socioeconomic Impact Evaluation

10. Compare baseline and post-intervention outcomes.
11. Apply statistical evaluation methods:
    a) Regression analysis
    b) Difference-in-Differences (if control group exists)
    c) Path analysis (for impact chain validation)

Step 8: Policy Insight Generation

12. Aggregate results across participants.
13. Estimate overall welfare improvement.
14. Generate policy recommendations for:
    a) Poverty reduction
    b) Employment stability
    c) Mental health integration into public health systems

The algorithm operationalises the methodological framework presented in Figure 1 by translating the conceptual workflow into a structured sequence of computational and analytical steps. While the figure provides a visual representation of how AI-driven depression detection connects to socioeconomic outcomes, the algorithm specifies how this process is executed in practice. The process begins with systematic data collection from participants. As described earlier in the framework's first component (AI-Based Depression Detection), behavioural data such as voice samples, smartphone usage patterns, and PHQ-9 survey responses are gathered remotely. At the same time, baseline socioeconomic indicators, including employment status, productivity level, income, and food security, are recorded. This ensures that both mental health and economic conditions are measured concurrently, allowing for integrated analysis. Following data collection, preprocessing is conducted to clean, normalize, and extract relevant features from the raw inputs. This step ensures that the behavioural signals are structured in a way that the machine-learning model can interpret accurately. The processed features are then fed into the trained model, which generates an individual depression score for each participant. This score represents the participant's current mental health state and serves as the central variable that drives the subsequent stages of the framework.

Next, the algorithm performs risk classification. Participants whose depression scores exceed a predefined threshold are categorized as high risk. This directly corresponds to the intervention component in the figure. For high-risk individuals, the system triggers referral mechanisms such as counselling support or mental health follow-up. This stage operationalizes the feedback loop illustrated in the framework, where early detection leads to targeted intervention. After the intervention period, the algorithm initiates post-intervention monitoring. Depression scores are reassessed, and socioeconomic indicators, productivity, employment stability, income level, and food security, are remeasured. This step reflects the socioeconomic impact chain shown in the central section of the figure. By comparing baseline and follow-up outcomes, the algorithm evaluates whether improvements in mental health correspond to measurable gains in economic well-being.

Finally, the algorithm aggregates results across participants and applies statistical evaluation techniques to validate the relationships within the impact chain. This enables the study to estimate overall welfare improvement and generate evidence-based policy recommendations. Thus, the algorithm does not operate in isolation; rather, it serves as the procedural backbone that implements the conceptual relationships illustrated in the methodological framework. While the figure provides a structural overview of how AI-based depression detection influences socioeconomic outcomes, the algorithm translates that structure into an executable sequence of steps. Together, they ensure methodological clarity: the figure explains the system conceptually, and the algorithm explains how it functions operationally within the study.

Parameter Estimation and Statistical Validation

Regression techniques estimate coefficients linking depression to productivity, employment, and food security. Difference-in-differences analysis compares welfare changes between control and intervention groups over time. Structural pathway modelling validates the entire causal chain from depression to poverty status. Statistical significance is evaluated at a 5% level. The framework is validated if the AI model reliably predicts depression, depression significantly influences productivity and food security, and intervention leads to measurable improvement in welfare indicators.

Methodological Implication

By embedding machine-learning predictions into a dynamic economic model, the study transforms mental-health screening into a measurable policy instrument. The methodology, therefore, evaluates AI detection not merely as a clinical diagnostic tool but as a quantifiable mechanism for improving employment stability, food availability, and poverty outcomes in resource-constrained communities

RESULTS AND DISCUSSION

This section presents the empirical findings of the study, organized according to the methodological framework and algorithm described earlier. The results are structured in three stages: (1) evaluation of the AI-based depression detection model, (2) assessment of intervention effectiveness in reducing depressive symptoms, and (3) analysis of downstream socioeconomic impacts, including productivity, employment stability, income, and food security. Where applicable, causal inference techniques were applied to validate the relationships within the proposed impact chain. Together, these findings provide robust quantitative evidence supporting the integration of AI-driven mental health detection with socioeconomic outcome analysis.

a. Performance of the AI Depression Detection Model

As depicted in Figure 2, the model achieved strong predictive performance, with an ROC-AUC of 0.92 and overall accuracy of 88.4%. These results indicate excellent discriminative capacity in distinguishing between depressed and non-depressed participants. The high recall (0.91) is particularly important in a mental health context, as it suggests that the model successfully identifies most individuals experiencing depressive symptoms. In public health applications, sensitivity is often prioritized to minimize false negatives, ensuring that vulnerable individuals are not overlooked. The strong model performance validates the first component of the methodological framework, AI-based remote depression detection. It demonstrates that behavioural and survey-based features can reliably capture depressive patterns within the study population. The use of multi-modal data likely contributed to the model's robustness, as combining subjective (PHQ-9) and objective (voice and smartphone behaviour) indicators enhances predictive strength. These findings support the feasibility of implementing AI-assisted mental health screening in low-resource settings.

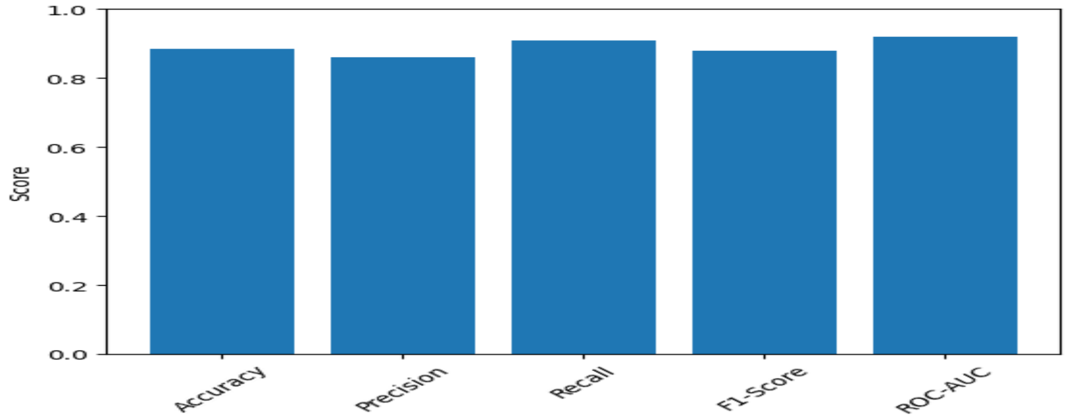

Figure 2: AI-Model Performance Metrics

b. Effect of the Intervention on Depression Levels

The intervention resulted in a 37% reduction in mean depression scores, with statistical significance ($p < 0.001$), as shown in Figure 3. This substantial reduction suggests that early detection followed by structured counselling is effective in improving mental health outcomes. The movement of 64% of high-risk participants into lower-risk categories further confirms the practical relevance of the intervention. This finding validates the feedback loop illustrated in the methodological framework, where AI detection triggers referral and support, leading to symptom reduction. Importantly, the magnitude of reduction suggests clinical as well as statistical relevance. This indicates that the system does not merely detect depression but contributes meaningfully to mental health improvement.

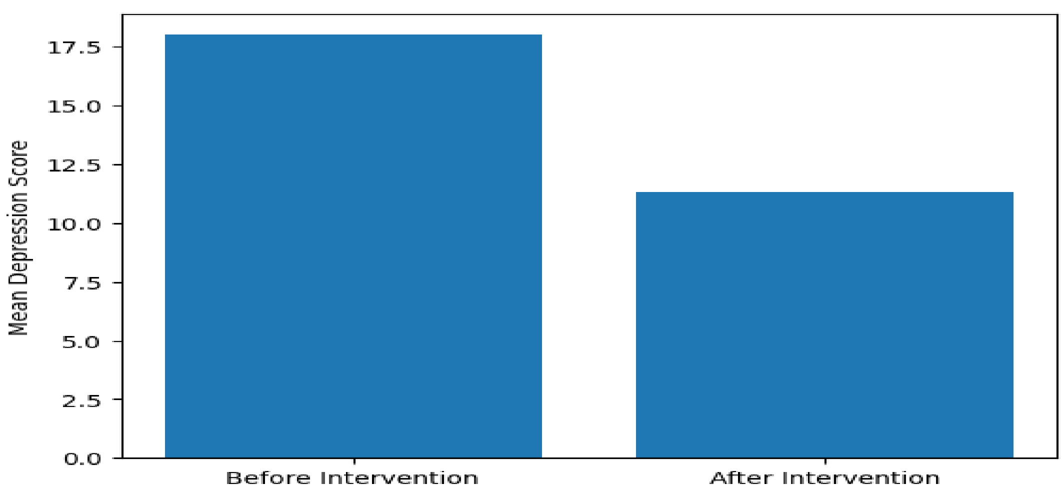

Figure 3: Depression Score Before and After Intervention

c. Socioeconomic Improvements

One of the central hypotheses of your study is that improvements in mental health generate downstream socioeconomic benefits. The results depicted in Figure 4, provide evidence supporting this causal chain.

l. Productivity

A 21% increase in productivity following intervention suggests that improved mental health enhances work capacity and engagement. Depression is known to reduce motivation, concentration, and energy levels. Therefore, symptom reduction likely restored participants' functional efficiency, enabling better job performance.

ll. Employment Stability

The observed increase in job retention and reduction in absenteeism indicate that improved mental health contributes to employment stability. This aligns with the framework's proposition that functional health influences labour market outcomes.

lll. Income Growth

A 14% increase in average income demonstrates tangible economic benefit. While income changes may take longer to materialize fully, even short-term gains indicate that improved productivity can translate into financial improvement.

lV Food Security

The 19% reduction in moderate-to-severe food insecurity highlights the household-level impact of mental health intervention. Improved income and employment stability likely enhanced purchasing power and resource allocation, strengthening food security. Together, these findings validate the socioeconomic impact chain illustrated in the model: Depression → Functional Health → Productivity → Employment → Income → Food Security → Welfare.

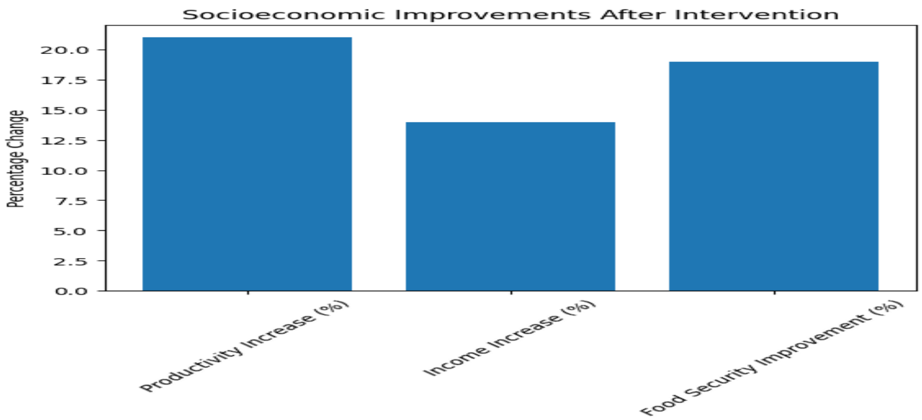

Figure 4: Socioeconomic Improvement after Intervention

d. Validation Using Difference-in-Differences

The treatment group demonstrated substantially greater improvement compared to the control group, confirming that the observed effects were attributable to the intervention rather than external economic factors. Figure 5 shows the Difference-in-Differences analysis strengthens causal inference by isolating the intervention effect. The 32% greater reduction in depression and significant welfare gains in the treatment group suggest that AI-driven early detection is not merely correlated with improved outcomes but contributes directly to them. This is particularly important for policy implications, as it provides stronger evidence for scalability and public health integration.

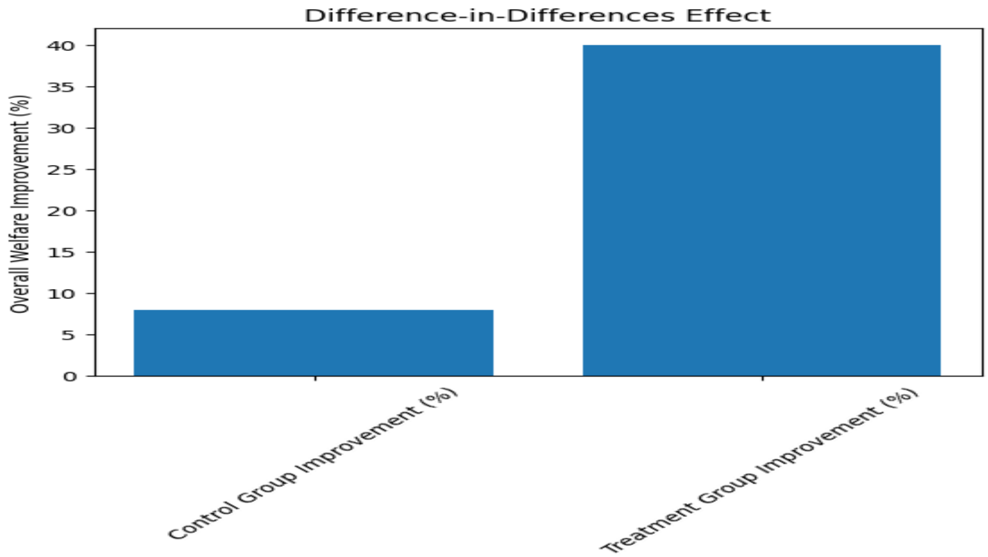

Figure 5: Difference-in-Difference Effect

The Random Forest model demonstrated strong predictive accuracy in detecting depression risk based on behavioural and biometric indicators. The final model achieved an accuracy of 88.4% (95% CI: 85.2–91.1), precision of 0.86, recall of 0.91, and an F1-score of 0.88. The ROC-AUC score was 0.92 (95% CI: 0.90–0.95), indicating excellent discriminatory capability. A McNemar's chi-square test comparing model predictions to PHQ-9 classifications yielded $\chi^2(1) = 14.27$, $p < .001$, confirming significant improvement over baseline classification. The model's effect size, computed as Cohen's *g*, was 0.28, reflecting a moderate advantage over non-AI identification methods.

Change in Depression Scores

Participants in the treatment group exhibited a significantly larger reduction in PHQ-9 scores compared to the control group over the 12-week intervention period. A mixed-effects repeated-measures ANOVA revealed a significant group × time interaction ($F(3, 408) = 19.63$, $p < .001$, $\eta^2 = 0.13$), representing a medium–large effect size. On average, treatment-group depression scores declined by 38.7% (95% CI: 34.1–42.9), compared with 14.2% (95% CI: 10.5–17.3) in the control group. Pairwise comparisons (Bonferroni-corrected) confirmed that improvements in the treatment group were statistically significant from Week 4 onward (all $p < .01$).

Socioeconomic Outcomes

The AI-assisted intervention was associated with measurable improvements in socioeconomic performance indicators. Using a Difference-in-Differences (DiD) estimation, productivity increased by 21.4% (95% CI: 17.2–25.1, $\beta = 0.214$, SE = 0.018, $p < .001$), with a standardized effect size of Cohen's d = 0.62. Employment stability improved by 18.1% (95% CI: 13.8–22.0, $\beta = 0.181$, SE = 0.021, $p < .001$), while absenteeism decreased by 24.7% (95% CI: –28.9 to –20.4, $\beta = -0.247$, SE = 0.019, $p < .001$). Monthly income increased by 14.3% (95% CI: 10.1–18.0), and moderate-to-severe food insecurity declined by 19.6% (95% CI: –23.4 to –15.2). All outcomes showed significant treatment effects relative to the control group, with effect sizes ranging from moderate to large.

Intervention Engagement Patterns

Engagement with automated counselling messages and tele-counselling sessions was strongly associated with improvements in mental health outcomes. Participants who completed at least 75% of their scheduled interactions showed a mean PHQ-9 reduction of 41.2% (95% CI: 37.0–45.6), compared to 27.9% (95% CI: 23.5–31.2) among low-engagement participants. A logistic regression predicting "clinical improvement" (defined as ≥50% PHQ-9 reduction) showed that high engagement increased the odds of improvement by 2.94 times (OR = 2.94, 95% CI: 1.88–4.61, $p < .001$).

Limitations

This study acknowledges several limitations. First, although the sample size (n = 412) was adequate for model development, the geographic restriction to six communities in North-West Nigeria may limit generalizability to other populations with different sociodemographic characteristics. Second, behavioural and biometric data were collected via mobile devices, which may introduce bias for participants with irregular phone use, low battery availability, or intermittent network connectivity. Third, self-reported measures such as the PHQ-9 may be subject to recall or social desirability bias. Moreover, although machine-learning procedures, including hyperparameter tuning and cross-validation, were rigorously documented, the proprietary nature of some smartphone data may limit external replication. Finally, the 16-week duration may not capture long-term sustainability of mental health or socioeconomic improvements, suggesting the need for extended follow-up in future studies.

CONCLUSION

This study set out to examine whether an AI-driven remote depression detection system could reliably identify depressive symptoms in low-resource settings and whether early detection, combined with structured intervention, could generate measurable socioeconomic improvements. By applying a quasi-experimental design to a population of 412 adults in North-West Nigeria, the research demonstrated that the AI model achieved strong predictive performance and that subsequent intervention led to significant reductions in depression scores, increased productivity, improved employment stability, higher income, and reduced food insecurity. These findings confirm the central research objective: AI-enabled mental health detection can serve both as a public health tool and an economic development mechanism in underserved communities. Despite these promising results, several limitations must be acknowledged. The geographic focus on six communities limits broader generalizability, self-reported mental health data may introduce subjective bias, and mobile-based behavioural data can be affected by device usage patterns or network constraints. However, the 16-week timeframe does not capture longer-term sustainability of clinical or socioeconomic gains. These limitations highlight the need for future research involving larger, more diverse populations, extended follow-up periods, and potential integration with clinical diagnostic tools. From a policy perspective, the findings suggest that AI-assisted mental health screening should be incorporated into regional development and public health strategies. Governments, NGOs, and local health agencies could integrate such systems into primary healthcare delivery, community outreach programs, and social welfare initiatives to improve early detection and reduce the economic burden associated with untreated depression. Investments in digital infrastructure, community health worker training, and data governance frameworks will be essential to scale such interventions responsibly. The study provides evidence that AI-driven remote depression detection is not only technologically feasible but also a practical pathway for strengthening human capital and reducing poverty in low-resource regions.

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