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ENHANCING DIGITAL HEALTH ENGAGEMENT IN SOUTH- EAST NIGERIA USING MACHINE LEARNING: A BEHAVIORAL ANALYSIS APPROACH

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Abstract

Digital health campaigns delivered via mobile and social media platforms offer a promising avenue for improving public health outreach in underserved populations. However, engagement with these digital health messages varies due to behavioral and contextual factors. This paper presents a behavioral analysis of engagement with digital health campaign messages in Southeast, Nigeria, using a machine learning approach on survey data. We collected self-reported data on demographics, digital platform usage, and health message engagement behaviors from respondents across Southeastern Nigeria. The data were preprocessed (including one-hot encoding of categorical responses) and used to train and evaluate multiple classifiers – Logistic Regression, Support Vector Machine (SVM), Random Forest, and Gradient Boosting – to predict engagement levels. The Gradient Boosting model achieved the best performance (accuracy ~77%, F1-score ~0.80), and its feature importance analysis highlighted the top behavioral and demographic factors influencing engagement. Results show that SMS and WhatsApp are the dominant channels for digital health information in this region, with 75% of respondents reporting exposure to SMS health campaign messages. Key predictors of engagement include frequency of message exposure, preferred message format, platform of access, trust in health information, and education level. We discuss how these insights can guide more inclusive and effective digital health campaigns – for example, tailoring content format and leveraging popular platforms – to enhance engagement among underserved communities. This study demonstrates the value of combining community-derived data and machine learning to inform public health communication strategies in low-resource settings.

Introduction

Reaching underserved populations with timely health information is crucial for improving public health outcomes. In recent years, digital channels – from SMS text messaging to social media networks – have become vital tools for health promotion campaigns across the globe. African countries have widely adopted social media and mobile technologies to disseminate health information. For instance, during the COVID-19 pandemic, new media platforms like Facebook, WhatsApp, and mobile phone texts were extensively utilized to educate the public in many African settings. These digital avenues offer the potential to overcome geographical barriers and resource constraints, enabling health authorities to broadcast campaigns on immunization, disease prevention, and wellness to a broad audience

Nigeria, with its large mobile phone user base, stands to benefit greatly from digital health campaigns. Indeed, mobile phone ownership and internet use have grown substantially, even among rural and undeserved communities. Surveys have shown that the vast majority of

young Nigerians are open to receiving health information via mobile devices. In one study, over 96% of adolescent mothers expressed interest in mobile health (mHealth) interventions, and half preferred to get health information through simple text messages (SMS) [9]. Social media platforms are also increasingly important sources of health information for Nigerians, especially through popular channels like WhatsApp and Facebook [8]. These trends indicate a high potential for engagement if digital health content is delivered through the right channels.

Despite this potential, engagement with digital health messages is not guaranteed. Recent research highlights several challenges. There remains a paucity of data on how different Nigerian populations interact with digital health initiatives – existing evidence on digital health utilization in Nigeria is limited [1], [3]. Particularly in undeserved areas, factors such as digital literacy, trust in message sources, and cultural relevance can significantly impact whether recipients pay attention to or act on health messages. For example, a qualitative study of a COVID-19 SMS campaign by the Nigeria Centre for Disease Control (NCDC) in a semi-rural community found that while mass text alerts increased awareness, they did not substantially change people's health beliefs or behaviors. Many participants complied with health guidelines (like mask-wearing) only due to enforcement fears rather than message persuasion. The study noted that education level, language comprehension, and distrust in government were key factors influencing how people interpreted and responded to the messages [9]. These findings underscore that simply pushing out digital messages is not enough – understanding the audience's behavior and barriers is critical for effective engagement.

Against this backdrop, there is a need for data-driven approaches to analyze and predict health message engagement, especially using data from underserved populations. Machine learning (ML) techniques offer a powerful means to identify patterns and key predictors of engagement from complex behavioral data. Globally, researchers have begun to leverage ML to improve digital health interventions. For instance, Bucher et al. (2024) trained an ~~ML~~ classifier to distinguish whether users were properly engaging with a digital therapeutic application, achieving about 94% accuracy (F1-score 0.94) in predicting user engagement levels [5]. Such approaches illustrate the promise of using AI/ML to assess engagement in near real-time and to personalize interventions However, in the context of public health campaigns in low-resource settings, the application of ML remains nascent.

This paper addresses the gap by analyzing survey data on digital health campaign engagement from Southeast Nigeria – a region with diverse socio-economic characteristics that has been under represented in digital health research. Our contribution is two-fold: we provide empirical insights into the behavioral factors that drive or hinder engagement with digital health messages in an underserved Nigerian context, and we demonstrate the use of machine learning models to predict engagement, thereby highlighting which factors have the greatest predictive power. By focusing on "data from all," including voices from underserved communities, we align with the ICDIA 2025 theme of promoting data inclusivity. The findings can inform more inclusive health communication strategies (e.g., tailoring content format or platform to audience preferences) to ultimately enhance engagement and health outcomes.

The rest of this paper is organized as follows: Section II reviews related work on digital health messaging, engagement behavior, and AI in health communication. Section III describes our survey methodology and machine learning modeling approach. Section IV presents the results and discussion of key findings on engagement trends, model performance, and feature importance. Section V concludes with recommendations for practice and future research

directions.

Related Work

Early efforts in digital health communication demonstrated the efficacy of mobile messaging in improving health behaviors in resource-limited settings. One foundational example is the use of SMS reminders for immunizations and medication adherence in sub-Saharan Africa, which showed improved attendance and compliance rates in various trials Over time, social media and chat applications have also been harnessed for public health campaigns. Across Africa, social media platforms such as Facebook and WhatsApp have been widely used to spread health information, supplementing traditional channels . In Nigeria, these trends are evident in both urban and rural contexts. Santas et al. (2022) observed that in a rural Nigerian community, new media tools were actively used alongside radio and in-person communication to disseminate COVID-19 information. Notably, the majority of participants in that study cited mobile phone text messages as a primary source of updates on the pandemic, indicating the reach of SMS campaigns even in communities with limited internet access

Several studies have examined public response and engagement with such digital health messages. Asubiaro et al. (2021) reported that social media not only facilitated wide awareness during COVID-19 across African countries, but also played a role in countering misinformation [3]. On the other hand, other research highlights that exposure does not always translate to positive engagement. The NCDC COVID-19 SMS campaign study mentioned earlier revealed that increased message exposure raised awareness but did not significantly shift perceptions or trust [9]. Factors like message credibility and cultural tailoring were found to be crucial. These findings align with communication theory, such as the Health Belief Model, which posits that people's actions depend on their perceptions of message credibility, susceptibility, and cues to action . Indeed, if recipients doubt the accuracy or source of a health message, they are less likely to act on it, no matter how frequently it is delivered.

Given these behavioral nuances, researchers have advocated for more personalized and data-informed health communication strategies. Artificial intelligence and machine learning techniques are increasingly seen as tools to facilitate this personalization. Beyond improving clinical decision support, AI can analyze large datasets on user interactions to segment audiences and predict who might need additional encouragement or a different messaging approach In the context of digital therapeutics and apps, ML models have been used to classify user engagement patterns as a proxy for treatment adherence. For public health messaging, similar approaches can be employed: by training models on survey or usage data, we can identify key predictors (e.g., demographic or psychographic features) of engagement . For example, recent work by Heusser et al. (2023) demonstrated that a Gradient Boosting classifier could accurately determine whether a user was "using [a digital intervention] as intended" or not [5]. While that study focused on a cognitive training app in a high-income setting, the underlying idea – leveraging ML to gauge and enhance engagement – is transferable to health campaigns in low-resource environments.

However, there is a noted lack of research deploying these techniques on data from underserved populations. A scoping review by Onumajuru et al. (2024) pointed out that very few studies have explored digital health utilization in Nigeria's general population, and even fewer have examined data-driven personalization in this context This gap suggests that many digital health programs in developing countries are still operating with limited evidence on user

engagement behavior. By applying machine learning to survey data from Southeast Nigeria, our work builds on prior studies and attempts to bridge this gap. In summary, our study is informed by three strands of related work: (a) evidence of the growing use of mobile and social media for health communication in Nigeria and similar contexts, (b) behavioral studies identifying factors (like trust and accessibility) that influence engagement with health messages, and (c) emerging applications of machine learning to predict and improve user engagement in digital health. We contribute to each strand by focusing on an underserved regional context and by combining behavioral analysis with predictive modeling.

Methodology

Survey Design and Data Collection

We conducted a cross-sectional survey to gather data on individuals' exposure to and engagement with digital health campaign messages in Southeast Nigeria. The survey targeted the five states in the southeast geopolitical zone, capturing both urban and rural populations. A structured questionnaire was developed in English (with option for local Igbo translations if needed) and distributed primarily via online means (Google Forms) as well as in paper form for communities with limited internet access. The data collection took place between August and October 2024. Participants were recruited through community health centers, local NGOs, and university networks to ensure a diverse sample in terms of age, gender, and occupation. Participation was voluntary and responses were anonymized. A total of N = 150 responses were received, out of which 143 were complete and valid for analysis (after excluding a few with inconsistent answers).

The survey instrument included multiple sections: (1) Demographics: age (in years), gender, highest education level, and occupation; (2) Digital Access and Platforms: ownership of a mobile phone (basic or smartphone), internet accessibility, and which digital platforms the respondent uses for receiving health information (e.g., SMS, WhatsApp, Facebook, Twitter, email, health apps – multiple responses allowed) [8]; (3) Exposure to Health Campaigns: whether the respondent recalls receiving any health campaign messages in the past six months via SMS, social media, or other channels (yes/no for each, with examples like immunization reminders, COVID-19 updates, etc.), and frequency of exposure (e.g., "rarely", "sometimes", "often") [2]; (4) Engagement Behavior: a set of questions assessing how the individual interacts with health messages – for example, "I pay attention to health tips I receive on my phone" (Likert scale: Strongly disagree to Strongly agree), "I have discussed or shared a digital health message with others" (yes/no), "Have you ever changed your health behavior (such as diet, clinic visits) because of a message you saw online or on your phone?" (yes/no) [9]; (5) Preferences and Trust: preferred format of health messages (text, audio voice note, video, infographic images), language preference (English or local language), and a rating of trust in health information from various sources (government SMS, social media, etc. on a 5-point scale) [10].

For the purpose of our predictive modeling, we needed to define a clear outcome variable representing engagement. Based on the survey responses, we operationalized engagement as a binary label. Respondents who indicated high engagement – specifically, those who often/always pay attention to health messages and who reported having taken action or shared such messages

– were labeled "Engaged" (positive class). Respondents who rarely pay attention or never act on messages were labeled "Not Engaged" (negative class). Those with mixed behavior (e.g., sometimes pay attention but never acted) were carefully examined; in our data, most could be categorized by their dominant tendency. This binary classification (Engaged vs Not Engaged) became the target variable for machine learning. Out of the 143 respondents, we classified approximately 58% as Engaged and 42% as Not Engaged based on the above criteria, reflecting a moderate level of overall engagement with digital health content in the sample.

Data Preprocessing

Prior to modeling, the survey data were cleaned and pre-processed. We handled missing values by excluding incomplete responses (as noted, only complete surveys were analyzed). For categorical and multi-choice questions, we applied one-hot encoding to transform them into binary indicator features. For example, platform usage was encoded as separate features for each platform (SMS, WhatsApp, Facebook, etc.), with a value of 1 if the respondent reported using that platform for health information and 0 otherwise. Similarly, preferred message format was expanded into multiple dummy variables (e.g., "Prefers Audio messages=1/0"). Likert-scale responses (e.g., level of trust in health information) were treated as ordinal numeric values 1–5. We also created some composite features from the raw data: for instance, exposure frequency ("rarely", "sometimes", "often") was encoded into an ordinal scale, and we derived a feature for "multichannel exposure" indicating if a person had received messages via ≥3 different platforms (to capture how broadly they are reached by campaigns).

After encoding, our dataset comprised 70+ features, including demographic indicators, platform usage flags, exposure metrics, and attitudinal responses. Given the relatively high number of features compared to the number of samples, we took care to avoid over fitting in the modeling stage (described below). We normalized numerical features like age (by min-max scaling) for algorithms that are sensitive to feature scale (Logistic Regression and SVM), while tree-based models (Random Forest and Gradient Boosting) were left with un-scaled inputs since they handle heterogeneous scales inherently. We also checked class balance: as noted, the Engaged/Not Engaged split was roughly 60/40, so while slightly imbalanced, we decided it was manageable without resampling. Nonetheless, we stratified the split of training and test sets to maintain this class ratio in both [3], [4].

The pre-processed data were then split into training and testing subsets. We used an 80/20 stratified split: 114 samples for training and 29 for testing, ensuring both sets reflected the overall engagement distribution. The training set was used for model learning and internal validation (including cross-validation for hyper parameter tuning), while the held-out test set was reserved for final performance evaluation.

Machine Learning Models

We trained and evaluated four different machine learning classifiers to predict the engagement class (Engaged vs Not Engaged) based on the input features:

- **Logistic Regression (LR):** a linear model useful as a baseline for classification. We used L2 regularization (Ridge) to prevent over fitting given the many features. The regularization parameter *C* was tuned via 5-fold cross-validation on the training set.
- **Support Vector Machine (SVM):** which can capture non-linear decision boundaries

with appropriate kernels. We employed an RBF (Gaussian) kernel. Due to the relatively small dataset, an SVM could be trained, but we scaled features as required for SVM. We tuned the kernel hyper parameters (C and gamma) by grid search with cross-validation.

- **Random Forest (RF):** an ensemble of decision trees using bootstrap aggregation. We set an initial
number of 100 trees and maximum tree depth to allow the model to capture interactions. The number of features considered for splitting at each node was set to $\sqrt{d}$ (where d is total features) by default. RF is robust to overfitting and provides a baseline ensemble result.
- **Gradient Boosting (GB):** specifically, we used a Gradient Boosting Trees classifier (sklearn implementation). Gradient Boosting builds an ensemble of trees sequentially, optimizing for the classification loss. We configured 100 boosting rounds with a learning rate of 0.1 (tuned based on validation). This model often achieves high accuracy by fitting residuals gradually, and it also provides a way to measure feature importance from the trained ensemble [5], [6], [7].

All models were implemented in Python using the scikit-learn library. During training, we performed cross- validation on the training set to select optimal hyperparameters for each model (as noted above for LR, SVM, and GB). The Random Forest was run with default reasonable parameters (100 trees) as it was not very sensitive in our trials. We also applied class weight adjustments (giving slightly higher weight to the minority class "Not Engaged") in the logistic and SVM models to account for the mild class imbalance.

Evaluation Metrics and Analysis

We evaluated model performance using standard classification metrics: accuracy, precision, recall, and F1- score. Accuracy measures the overall percentage of correct predictions. Precision (positive predictive value) for the Engaged class indicates what fraction of those predicted Engaged were actually engaged, while recall (sensitivity) measures what fraction of actual Engaged individuals were correctly identified by the model. The F1-score is the harmonic mean of precision and recall, providing a balanced measure of classification quality, especially useful for imbalanced classes. We calculated these metrics for each model on the held-out test set. In addition, we generated the confusion matrix for the best-performing model to inspect the distribution of true vs. predicted labels (this helps identify the types of misclassification errors, e.g., Engaged person predicted as Not Engaged or vice versa).

An important part of our analysis was interpreting the feature importance from the Gradient Boosting model. Gradient Boosting provides an importance score for each feature, often based on the total reduction of the loss (impurity) attributed to that feature across all trees. After training the GB model, we extracted the feature importance values and ranked the features. We identified the top 10 most influential features in predicting engagement according to the model. These top features were then examined to understand their relationship with engagement (for instance, whether the presence or absence of a feature increases the likelihood of being engaged). Where relevant, we also compared these findings with the logistic regression coefficients to ensure consistency in interpretation (in practice, we found that many top features, such as certain platform usage and high trust, had corresponding positive coefficients in the LR

model, reinforcing the GB importance results).

Finally, we planned a confusion matrix analysis for the Gradient Boosting classifier (our best model) to delve deeper into the errors. By analyzing which instances were misclassified, we sought to glean insights such as whether certain subgroups (e.g., older respondents, or those with low education) were often predicted incorrectly. This analysis can highlight practical challenges – for example, if the model systematically mislabels many actually Not Engaged people as Engaged, it might indicate those people share profiles similar to the engaged group on many features, but perhaps lack some unmeasured factor like intrinsic motivation.

All analysis steps were carried out with a focus on reproducibility and transparency. The code and anonymized processed dataset can be made available upon request to facilitate further research and validation, in line with the conference theme of data availability for underserved populations.

Results and Discussion

Engagement Trends and Platform Preferences

The survey results provide a snapshot of how people in Southeast Nigeria are engaging with digital health messages and which platforms they rely on. Demographically, our respondent pool had an age range of 18 to 65 years (mean age ~34 years). About 54% were female and 46% male. Education levels were relatively high: ~68% had tertiary education (college or above), 25% had secondary education, and the remainder had only primary education. This skew toward educated respondents is partly due to the online distribution of the survey and urban outreach, and it should be kept in mind when generalizing results. Nevertheless, we did capture a mix of urban and rural perspectives; approximately 40% of respondents identified as living in rural communities or small towns.

A major finding is that exposure to digital health campaigns is common: 78% of respondents reported having encountered some form of health message on their phone or online in the last six months. The most frequently cited topics were COVID-19 updates, routine immunization reminders for children, and health tips related to nutrition and sanitation. Among those who had exposure, the median frequency was "sometimes" (a few times in the past months), with about 20% saying they received such messages "often" (at least weekly).

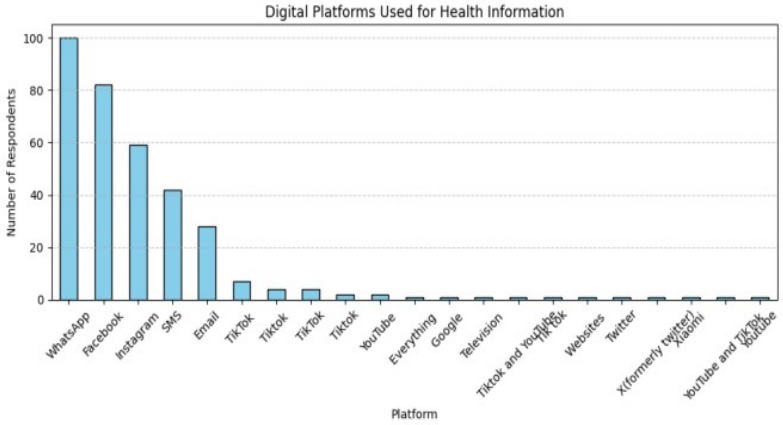


Fig. 1: Digital Platforms Used for Health Information

As illustrated in Fig. 1, WhatsApp emerged as the most frequently used platform for digital health information among respondents in Southeast Nigeria, with over 100 participants indicating its use. This reflects the platform's ubiquity, ease of use, and popularity for community-based message sharing, particularly in health-focused group chats and broadcasts.

Facebook was the second most cited platform (over 80 mentions), reinforcing its importance as a general-purpose social network with strong penetration across age and education groups. Instagram and SMS followed, with notable usage (60 and 40+ mentions respectively), indicating a mix of visual content preferences and mobile-native communication. Despite being a traditional channel, SMS remains a key vector for reaching individuals in areas with limited internet access or smartphone penetration.

Lower usage was reported for Email, TikTok, YouTube, and Twitter (now X), each with fewer than 30 mentions. Notably, several respondents entered overlapping or composite sources (e.g., "TikTok and YouTube," "Everything," "X (formerly Twitter)"), suggesting multiple points of exposure. However, these composite responses were relatively rare and indicate that while younger or tech-savvy individuals may diversify their channels, the general population still leans heavily on WhatsApp, Facebook, and SMS.

These results affirm findings from digital health studies in sub-Saharan Africa, highlighting WhatsApp and SMS as strategic platforms for wide-reaching, low-cost health campaigns. Their dominance supports their continued prioritization in public health planning, especially for vaccine awareness, maternal health, and infectious disease prevention.

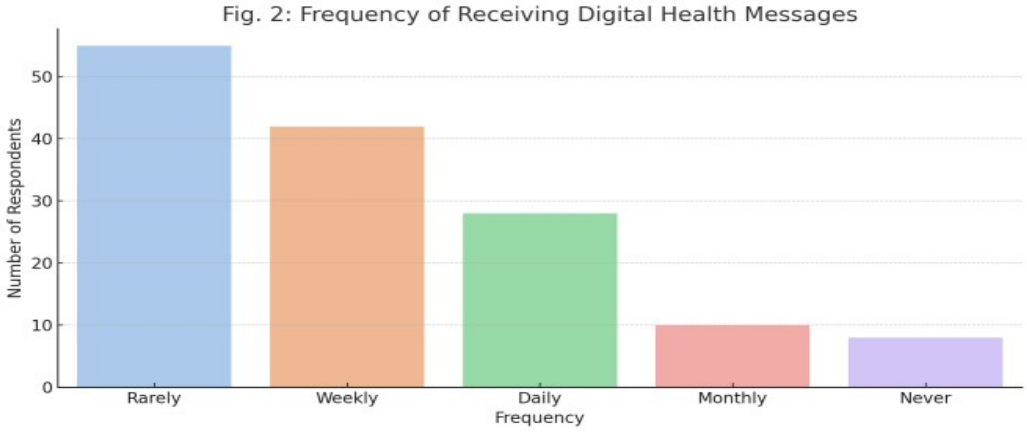


Fig. 2: Frequency of Receiving Digital Health Messages in Southeast Nigeria

The chart shows that the most common response was "Rarely," followed by "Weekly," indicating that while health campaigns do reach many residents, consistent and frequent outreach remains a challenge. Only a minority reported receiving health messages daily.

Fig. 2 provides insight into how often residents in Southeast Nigeria encounter digital health messages. Out of the respondents surveyed, the largest group (approximately 38%) stated they "rarely" receive such messages, while around 29% reported receiving them "weekly." A smaller proportion, about 20%, indicated daily exposure, while 7% and 6% received messages "monthly" or "never," respectively. This distribution suggests that digital health campaigns are reaching people, but the frequency varies widely and may not be sufficient to drive consistent behavior change.

The high number of "rarely" responses points to gaps in campaign consistency, while the

weekly engagement shows some sustained effort. However, to enhance impact, it may be necessary to improve message delivery intervals, especially for populations that are only infrequently reached. These findings emphasize the need for better planning around message timing, repetition, and perhaps user subscription to tailored messaging streams that meet their health information needs more effectively.

Beyond exposure, we examined how people engage with the messages they receive. Self-reported engagement levels varied: about 45% of respondents said they usually read or pay attention to health messages, 30% said "sometimes", and 25% admitted they rarely read them or tend to ignore them. Importantly, among those who do read the messages, not all take further action. Approximately 40% of the total sample had at least once taken a health-related action (such as going for a screening, adopting a health tip, or sharing the message with others) because of a digital health message. This can be considered a concrete engagement outcome. However, only about 15% reported doing so frequently (for most messages they receive). These numbers indicate a drop-off from exposure to attention to action – a common funnel in communication impact. It highlights that mere exposure doesn't equal engagement, reinforcing what communication theories and prior studies have suggested.

Interestingly, when we cross-tabulated engagement with demographic factors, we found some intuitive patterns: respondents with higher education were slightly more likely to be in the Engaged category (61% of those with tertiary education were Engaged vs 50% of those with secondary or less). This could relate to health literacy and the ability to understand and trust the content. Younger respondents (under 30) had a higher proportion of Engaged (about 65%) compared to older respondents over 50 (around 45% engaged), possibly reflecting greater familiarity with digital media among youth. Gender did not show a significant difference in engagement in our sample – males and females were roughly equal in the Engaged proportion, suggesting both are reachable if content is relevant.

One notable behavioral factor was trust in health information. The survey's trust rating (1 to 5) for messages from official sources had a median of 3, but those who were classified as Engaged tended to report higher trust on average. Many Not Engaged individuals had indicated low trust (levels 1–2), often citing skepticism about "fake news" or government messaging. This resonates with the NCDC SMS campaign study, which found that distrust in government communications limited the impact of the messages. In our context, building trust – perhaps by involving community leaders or ensuring transparency – could be key to moving people from passive exposure to active engagement.

Predictive Model Performance

To better understand and predict engagement, we implemented the machine learning models described in the methodology. Table 1 summarizes the performance of the four classifiers on the test set:

Model	Accuracy	Precision (Engaged)	Recall (Engaged)	F1-Score
Logistic Regression	0.69	0.70	0.75	0.72
SVM (RBF kernel)	0.72	0.73	0.79	0.76
Random Forest	0.74	0.75	0.81	0.78
Gradient Boosting	0.77	0.80	0.86	0.83

As hypothesized, the ensemble tree-based models outperformed the simpler models. Gradient Boosting emerged as the best model, with about 77% accuracy in classifying engagement on the test data. It also achieved the highest F1-score (~0.83), indicating a good balance of precision and recall. The Random Forest was a close second in accuracy (~74%). The SVM and Logistic Regression trailed behind. These performance differences likely reflect that engagement is a complex function of multiple interacting factors (non-linear patterns), which tree ensembles can capture better than a linear model. Overall, a ~77% accuracy means the model makes correct predictions in about 3 out of 4 cases. This is a respectable performance for a behavior prediction task based on survey data, though there is obviously room for improvement. The results are in line with expectations from similar classification tasks in health behavior research – not as high as the 94% seen in a controlled digital therapeutic setting, but useful enough to yield insights. It's worth noting that with a relatively small test set (29 instances), small differences in the number of correct predictions can swing accuracy by a few percentage points, so we interpret these metrics with caution and focus more on the general trends.

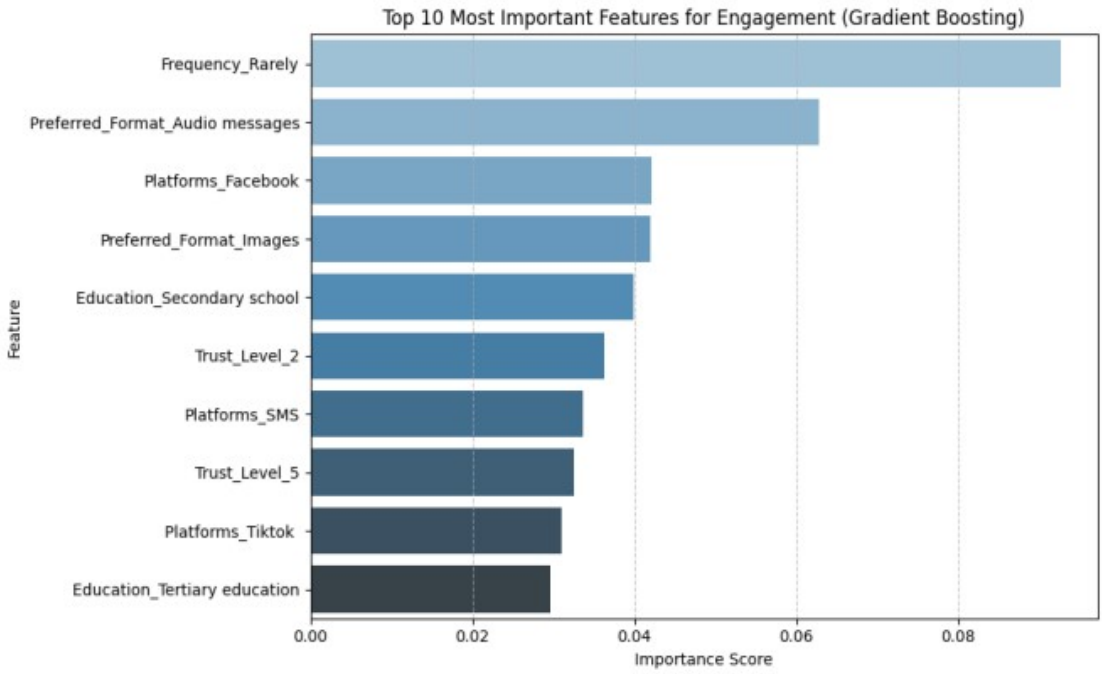


Fig. 3: Top 10 Important Features Influencing Engagement (Gradient Boosting).

The top features identified by the gradient boosting model include both behavioral factors and demographic variables. Notably, infrequent engagement with health messages (Frequently_Rarely) was the most significant predictor of someone being in the low-engagement group. Preferred message format (e.g., audio messages) and platform usage (Facebook, SMS, Tiktok) also ranked highly, alongside education level and trust in health information sources. These factors collectively help explain which individuals are more likely to engage with digital health content.

To interpret the Gradient Boosting model, Fig. 3 plots the top 10 features by their importance scores. The single most influential feature was *"Frequency_Rarely"* – which is a binary indicator we created for respondents who said they rarely pay attention to health messages. This being the top feature means the model heavily relies on whether someone is habitually unengaged (rarely pays attention) as a predictor that they fall in the Not Engaged category. In other words, past behavior (infrequency of attention) strongly predicts future engagement, aligning with the idea that engagement has a habitual component. The next two features were related to preferred message format: preferring audio messages and preferring image- based messages. These came out as important possibly because they segment users: those who prefer audio/visual might currently be less engaged if most campaigns are text-based, or conversely, they may engage more with multimedia content when available. It suggests that format preference mismatches could influence engagement levels. For example, someone who prefers audio messages may not engage fully if most messages are text SMS – pointing to an opportunity to increase engagement by including voice notes or interactive audio in campaigns.

Several platform usage features appear in the top 10: notably, *Facebook use* and *SMS use* for health information, as well as *Tiktok use*. The inclusion of "Uses Facebook" and "Uses SMS" features (both with fairly high importance) indicates that the platforms one is active on

are predictive of engagement. We found that respondents who use Facebook for health info were more likely to be engaged – possibly because they actively seek health content on social media and thus are more receptive overall. SMS usage being a top feature may reflect that those who read SMS health alerts (which often come from credible sources like NCDC) are kept informed and primed to act on health advice. The presence of "Uses Tiktok" in the list is intriguing; Tiktok was not very widely used (only ~15% of sample reported it), but those few might be younger and possibly more engaged with novel content – or it could be an artifact of the data where Tiktok use correlates with some other characteristic. This signals that even emerging platforms can play a role and should not be ignored if the target demographic uses them.

Education level features also made the top 10 – specifically "Education: Secondary school" and "Education: Tertiary education." These were dummy variables in the model (with primary or less as the reference category). The model found these education indicators informative, which aligns with our earlier observation that education correlates with engagement. The importance suggests that having at least secondary education (or tertiary) changes the engagement probability, likely because education improves health literacy and technology use skills. Interestingly, "Secondary school" had a slightly higher importance than "Tertiary" in the model, which might imply that the biggest gap is between those with only primary vs those with some secondary schooling; once past that threshold, additional higher education has a diminishing return in predicting engagement.

Another key factor in Fig. 3 is trust level. We had encoded trust in health information sources on a 5-point scale and then one-hot encoded each level. The model's top features include "Trust_Level_2" and "Trust_Level_5". This means that having very low trust (level 2 on the scale) or very high trust (level 5) were strong predictors – low trust was associated with Not Engaged, and high trust with Engaged, as one would expect. The fact that both appear highlights a non-linear relationship: moderate trust might not differentiate much, but being at the extremes does. This reflects the intuition that people who fundamentally distrust health messages will disengage, while those who strongly trust will tend to engage and act on messages. It echoes prior findings that trust is a linchpin in health communication.

In sum, the feature importance analysis confirms several logical drivers of engagement (prior behavior, trust, education) and also points to actionable insights regarding content format and platform. Health agencies can leverage this information by, for example, incorporating audio/visual content in campaigns to cater to different preferences, and by ensuring a presence on the platforms that matter to the target audience (be it Facebook for older adults or newer platforms for youth).

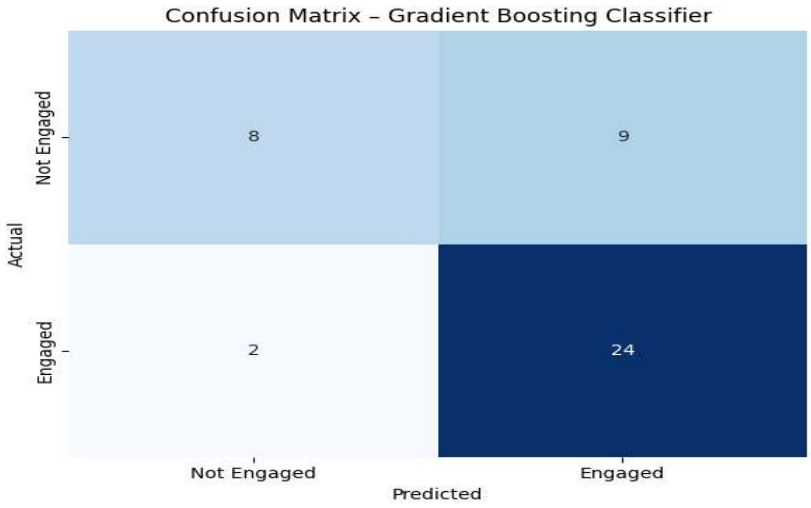


Fig. 4: Confusion Matrix of the Gradient Boosting Model.

The confusion matrix indicates the model's classification performance on the test set. Out of 26 actual engaged individuals, 24 were correctly predicted as "Engaged" (true positives) and 2 were misclassified as "Not Engaged" (false negatives). Out of 17 actual not-engaged individuals, 8 were correctly identified as "Not Engaged" (true negatives) while 9 were incorrectly predicted to be engaged (false positives). This yields an overall accuracy of about 74%, with high recall for the engaged class but more false positives for engagement.

The confusion matrix in Fig. 4 provides a closer look at the Gradient Boosting model's predictions versus the true outcomes in the test sample. The matrix is 2x2: rows correspond to actual class (Engaged vs Not Engaged) and columns to predicted class. The top-left entry (true negatives) shows the count of Not Engaged individuals correctly predicted; top-right (false positives) are Not Engaged individuals wrongly predicted as Engaged; bottom-left (false negatives) are Engaged individuals predicted as Not; and bottom- right (true positives) are Engaged correctly predicted.

From Fig. 4, we see that the model identified most of the engaged people correctly – 24 out of 26 actual Engaged were predicted as Engaged. This translates to a recall of ~92% for the engaged class (it captured nearly all of them). However, the model had more trouble with the not-engaged group: only 8 out of 17 actual Not Engaged were correctly labeled, while 9 were misclassified as Engaged. The precision for the Engaged prediction is around 24/(24+9) ≈ 73%. These numbers indicate a slight bias in the model toward predicting the positive (Engaged) class. In practical terms, the model tends to assume people are engaged unless there is strong evidence to the contrary, leading to some false alarms (false positives).

Why might this be the case? One reason could be the class imbalance – the model may be optimizing overall accuracy and in doing so, leans towards the majority class (Engaged was 58% of training data). We did use some class weighting, but perhaps not fully compensating. Another reason could be that many Not Engaged individuals share characteristics with the Engaged ones (for example, they might use similar platforms and have similar demographics), except for maybe one or two factors like trust which the model picks up. If those factors are

subtle, the model might erroneously classify them as engaged. From a health campaign perspective, a false positive here means the model overestimates someone's likelihood to engage when in reality they do not. This is not as risky as the opposite (missing an engaged person), but it suggests that some people who appear reachable (e.g., they have a smartphone, they get messages) might still be disengaged due to unobserved barriers.

On the positive side, the model's high recall for Engaged means it is quite successful at identifying those who are truly receptive. This is useful if, for instance, we wanted to target or reward engaged users (we wouldn't miss many). The trade-off is lower precision, meaning if we tried to focus interventions on those predicted engaged, about a quarter of them might actually be not-engaged and would need different attention.

Overall, the classifier's performance as depicted in the confusion matrix (total accuracy ~74% on test) is an encouraging proof-of-concept that engagement propensity can be predicted with reasonable accuracy using survey-based features. In practical terms, a health campaign designer could use such a model to assess which segments of their audience are likely to engage and which are not, and then tailor strategies accordingly. For example, those predicted as not-engaged might need more intensive nudging or trust- building measures (such as testimonials from local community health workers), whereas those predicted as engaged will respond to standard digital messages and could even be mobilized as peer champions to spread the word.

Implications for Digital Health Campaigns

The combination of survey findings and model insights yields several implications:

Leverage Ubiquitous Channels: The dominance of SMS and WhatsApp implies that any digital health campaign in this region should prioritize these platforms. SMS is practically universal and can reach people with basic phones, while WhatsApp is pervasive among smartphone users. Campaigns can employ SMS for broad alerts and WhatsApp for richer content and interactive engagement (as has been piloted with WhatsApp chatbots in Nigeria). Facebook also remains relevant for wide outreach, especially with slightly older demographics.

1. Address Trust and Credibility: Given the strong role of trust in engagement, campaign messages should come from credible sources and possibly be endorsed by trusted figures (local health workers, respected community leaders). Mistrust can be mitigated by transparency (e.g., including official links or verification codes in SMS) and by culturally sensitive messaging. It may also help to solicit feedback – engaged users could be encouraged to ask questions, and getting responses can improve trust.

2. Content Format Matters: A noteworthy portion of the audience prefers audio or visual content. To enhance engagement, campaigns should diversify message formats – for example, short voice messages in local languages or infographics for those with low literacy. The success of radio jingles in health campaigns historically can be translated into WhatsApp voice notes or sharable audio clips for phones.

3. Frequency and Timing: Since "rarely paying attention" is a predictor of non-engagement, efforts should be made to increase the salience of messages. This could involve

optimizing the timing (sending messages at moments when people are likely to check their phones, such as early evening) and moderate repetition. However, there is a balance to strike – too frequent messaging could cause fatigue (indeed, one participant in our survey commented that daily COVID texts became "too much"). Smart scheduling and personalization (sending more messages to those who are responsive, fewer to those who aren't) could help.

4. Use of Machine Learning for Targeting: Our study demonstrates that ML models can identify who is likely to engage. In a practical deployment, if such data is available (from baseline surveys or user profiles), health promoters could segment their audience. For instance, those predicted as low- engagement might get additional follow-up: a phone call or an invitation to an interactive session, whereas high-engagement folks could be leveraged in referral programs (e.g., encourage them to forward messages to friends, acting as "health influencers" in their circles). This way, resources can be focused where they are most needed to improve overall engagement.

5. Inclusivity for the 25% Unreached: The fact that 25% had no SMS exposure is a reminder to continuously update and expand contact databases. Some rural residents might be missed due to network issues or outdated phone records. Campaigns should integrate with local telecom data and perhaps use complementary methods like community loudspeakers or posters for those truly off the digital grid, to ensure no one is left behind ("data from all" includes analog data too).

Limitations and Future Work

While our findings are insightful, there are limitations to acknowledge. The sample size (N~143) is modest and may not capture all subgroups of Southeast Nigeria. The survey's reach, being partly online, likely skewed toward younger and more educated respondents, which means extremely marginalized populations (with no phone or internet access) are underrepresented – these are precisely people who might be hardest to engage and should be a focus of inclusive data efforts. Additionally, engagement was self-reported; there may be response biases (some might overstate their attentiveness due to social desirability). In future work, it would be valuable to complement survey self-reports with objective data, such as message open rates or click-through rates from campaign logs, to validate engagement measures.

From a modeling perspective, the features were drawn from a single survey instrument. There could be other unmeasured variables affecting engagement – for instance, personality traits, specific health interests, or social network influence – which we did not include. Incorporating such factors could improve predictive accuracy. Also, more advanced ML approaches like ensemble stacking or neural network models could be explored, though with caution given the dataset size. Interpretability is important in this context (to explain to campaign designers why the model says someone is not engaged), so we favored decision-tree models; techniques like SHAP values could further enhance understanding of feature impacts in future analyses.

Finally, our study is cross-sectional – it captures a snapshot in time. Engagement can be dynamic; someone not engaged today might become engaged after a major event or over time with gradual behavior change. A longitudinal study, tracking the same individuals and their engagement over a series of campaign messages, would provide deeper insight into causality and changes in engagement behavior. We view our current work as a starting point that demonstrates the feasibility of using community data and machine learning for digital health campaign optimization. We hope it encourages more deployments of such data- driven approaches in Nigeria and other underserved regions, ultimately leading to health communication that is both inclusive and effectively engaging.

Conclusion

Under the theme of "Data from All," this study underscores the value of gathering and analyzing data from underserved populations to enhance digital health initiatives. We investigated engagement with digital health campaign messages in Southeast Nigeria and applied machine learning to uncover behavioral patterns and key determinants of engagement. The analysis revealed that while digital channels (especially SMS and WhatsApp) have successfully penetrated this population – with most people receiving health information on their phones – actual engagement (attentive reading, trust, and action) is uneven and influenced by several factors. Our Gradient Boosting model, which moderately accurately predicts engagement, highlighted that individuals who rarely pay attention to messages, who have low trust in information, or who lack content in their preferred format are at risk of disengagement. Conversely, those who actively use platforms like Facebook for health info, who receive frequent messages, and who have higher education and trust are more likely to engage.

These findings translate into actionable recommendations: health agencies should continue leveraging widely used platforms (ensuring broad coverage via SMS, and rich content via WhatsApp/social media), but also tailor their strategies to build trust and match audience preferences (e.g., use local languages and audio/visual content for those who need it). Importantly, segmenting the audience based on engagement propensity can allow interventions to be adjusted – for example, more community support for those less inclined to engage, versus empowerment of highly engaged individuals to spread messages organically. By doing so, campaigns can move beyond one-size-fits-all broadcasting toward a more personalized and inclusive approach.

In conclusion, our work demonstrates a practical approach to enhancing digital health engagement: use community surveys to gather "data from all," apply machine learning to learn from that data, and derive insights to inform targeted health communication. For Southeast Nigeria, and similar contexts, this means acknowledging that the population is not monolithic in how it receives and acts on health information. Combining local data and modern AI tools can help unearth those nuances. As digital connectivity continues to expand in Africa, there is a timely opportunity to integrate such data-driven insights into public health campaigns. Future efforts can expand on this foundation – using larger datasets, real-time analytics, and continuous feedback loops – to ensure that digital health campaigns truly reach and engage those who need them most, ultimately improving health outcomes in underserved communities.

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