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Sentiment and Thematic Analysis of User Feedback from Integrated Wearable and Contact Tracing Application in Nigeria

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ABSTRACT

This study evaluates user experiences with *Tracy*, an integrated contact tracing and health monitoring system consisting of a wearable device and a mobile application. The wearable tracks physiological indicators such as body temperature and heart rate, while the application supports location-based contact tracing and movement analysis. Feedback was collected from 128 participants who used the system over a defined period. User responses were analysed through text preparation, thematic identification, and sentiment evaluation to understand user perceptions and willingness for continued use. Four major themes emerged from the analysis: usability, performance, content and features, and engagement and interest. Results revealed strong positive perceptions of usability and engagement, while performance and content highlighted areas requiring improvement. A substantial portion of feedback could not be classified into predefined themes, indicating the need for more structured feedback mechanisms. Overall, positive user experience was strongly associated with willingness to reuse the system. These findings emphasize the importance of user-centered design, technical reliability, and efficient system integration in the development of mobile health technologies in resource-constrained settings such as Nigeria.

Keywords: Sentiment analysis; Digital health technology; Wearable sensors; Contact tracing app; mHealth adoption; Community health surveillance

Introduction

The global health landscape has witnessed a significant transformation in recent years driven by advancements in digital health tools, particularly mobile health (mHealth) applications and wearable devices (Carey *et al.* 2016). These technologies have proven crucial in enabling real-time health monitoring, early detection of infectious diseases, and improving communication between individuals and health authorities (Ojokoh *et al.*, 2022). The rapid global deployment of mobile contact tracing apps during the COVID-19 pandemic represented a landmark moment in digital public health, offering a potential technological solution to curb disease transmission (Ferretti *et al.*, 2020; Whitelaw *et al.*, 2020). These apps aimed to

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automate the identification of exposure events and notify users of potential infection risks, theoretically enabling faster and more efficient containment than manual contact tracing alone. Integrated systems that combine physiological sensing with geolocation-based monitoring have emerged as promising tools for epidemic preparedness and response (Specht *et al*., 2025).

Despite the effectiveness of integrated digital health systems, their success depends largely on user acceptance and usability, two critical dimensions that influence sustained engagement. Poorly designed or culturally mismatched tools often suffer from low uptake and abandonment, rendering them ineffective in real-world applications. Research by Leung *et al*. (2024) on the Dutch CoronaMelder app highlighted that even robust systems can have limited epidemiological impact if not widely used. This underscores a growing imperative to ensure that health technologies are not only technically sound but also socially and behaviorally aligned with the targeted users. Also, earlier research focused on technical performance metrics like Bluetooth accuracy and privacy safeguards (Abeler *et al*., 2020), less attention was paid to understanding the holistic user experience, including usability, feature relevance, and emotional engagement, that ultimately determined real-world adoption and effectiveness (Walrave *et al*., 2022; Zhang *et al*., 2021).

However, low and middle-income countries (LMICs) such as Nigeria face unique barriers to digital health technology adoption. For instance, bad power supply and high data costs are persistent issues in Nigeria, often limiting the sustained use of mobile apps even when users are initially enthusiastic. With a population exceeding 220 million and significant portions living in rural or underserved regions, Nigeria's health infrastructure remains unevenly distributed. Limited digital literacy, inconsistent network coverage, and concerns about data security further complicate the uptake of mHealth tools. These challenges necessitate solutions that are both technically robust and attuned to local socioeconomic and cultural conditions. Prior research has shown that poorly contextualized health apps often fail due to usability flaws. Saeidnia *et al*. (2023) observed that most mHealth applications used during the COVID-19 pandemic were often hindered by complex interfaces and inadequate onboarding, especially in LMICs. Similarly, Hu *et al*. (2024), in a bibliometric review of wearable health device studies, emphasized that usability encompassing comfort, reliability, and functionality is a major bottleneck in the adoption of wearable technologies. These findings point to the need for iterative, user-centered design strategies, particularly in countries like Nigeria where first-time technology use remains common.

Similarly, recent national studies further support the potential of mobile health tools in Nigeria. Ojokoh *et al*. (2024) evaluated a digital contact tracing framework during COVID-19 and reported adoption rates ranging from 69.7% to 93.8% across different geopolitical zones. While privacy concerns were significant (71.6% of participants), a majority expressed interest in features like daily infection rate updates. These findings suggest a growing openness among Nigerians to engage with mobile health interventions, provided that issues of trust, data protection, and relevance are addressed. Musa *et al*. (2024) piloted a Bluetooth- and GPS-enabled contact tracing app with tuberculosis patients in Lagos, Nigeria. Despite limitations in sample size and correlation strength, the study demonstrated that meaningful contact data could be collected without violating user privacy. This aligns with broader trends toward integrated digital systems capable of both preventive and reactive health surveillance. Their work set the stage for broader studies by highlighting the feasibility of localized, privacy-aware contact tracing solutions in Nigeria.

Furthermore, in response to these contextual needs and building on prior efforts, the present study introduces *Tracy*, an integrated digital health system combining an IoT-based wearable device and a mobile application for contact tracing. The wearable monitors physiological metrics such as body temperature and heart rate, while the mobile app facilitates geospatial tracing and movement analysis. This dual functionality enables both health monitoring and early warning in the event of disease exposure. The system was piloted in Nigeria and obtained responses about the end users' experience. Analyzing user feedback presents an opportunity to understand experiential factors for contact tracing. Existing approaches often rely on black-box machine learning models that lack transparency for public health stakeholders (Rödseth *et al*., 2023). Recent work in natural language processing has demonstrated the value of combining topic modeling with sentiment analysis for health app evaluation (Hussein *et al*., 2023; Lau *et al*., 2022), but few studies have applied these methods to contact tracing apps specifically. Moreover, the field lacks standardized frameworks that balance computational efficiency with interpretability, particularly for moderate-sized datasets where complex deep learning approaches may be unnecessary or impractical (Klein *et al*., 2021). This gap is significant because public health agencies and app developers need clear, actionable insights, not just statistical patterns, to iteratively improve digital tools.

This study addresses these limitations by developing and applying a three-stage analytical framework to user feedback from *Tracy* contact tracing app. Building on established methodologies in digital health (Budd *et al*., 2020) and NLP-driven feedback analysis (Lau *et al*., 2022), we combine rule-based thematic classification with sentiment scoring to bridge the divide between computational efficiency and human interpretability. Our data-driven approach uniquely evaluates both single- and multi-theme assignment strategies to capture the multidimensional nature of user feedback, while explicitly linking themes to behavioral outcomes described as willingness to participate in future public health initiatives. The resulting framework offers public health practitioners a practical tool for continuous app improvement, filling a critical gap between academic research and real-world implementation (Rowe, 2020). By analysing empirical feedback from participants, the study identifies both strengths and limitations of the system in its current form. In doing so, it aims to provide actionable insights for improving the system before broader deployment and longer-term testing. The overarching goal is to inform the development of user-centered, context-appropriate digital health tools that can contribute meaningfully to epidemic preparedness and response in Nigeria and similar low- and middle-income countries. Unlike previous studies that majorly examined either technical feasibility or adoption in isolation, this study uniquely combines sentiment analysis with thematic categorization to capture the raw emotions and functional dimensions of user experience. Through this work, we contribute to the growing body of research on mHealth and wearable technologies, emphasizing the critical role of human-centered design, iterative refinement, and local user engagement in achieving scalable digital health solutions.

Methodology

The methodology for analysing users' responses from the mobile contact tracing app is explained in this section, which includes several steps, from preprocessing to analysis, to reveal users' behaviour towards the app. Figure 1 describes the systematic approach for analysing comments from users of the contact tracing app. The analysis is divided into three stages: the first stage is initialisation, which involves data collection and preprocessing. The second stage is theme processing, which involves generating themes from topics and building keywords for themes. Sentiment processing is the third stage that processes comments in each theme as either positive, negative or neutral.

Data Collection

The comments were gathered from an In-app feedback form in a research study that collected information including: the identification number, email, comment/response, and decision to use the app. All the records of all comments were saved in the database and exported as a single Excel file for further processing.

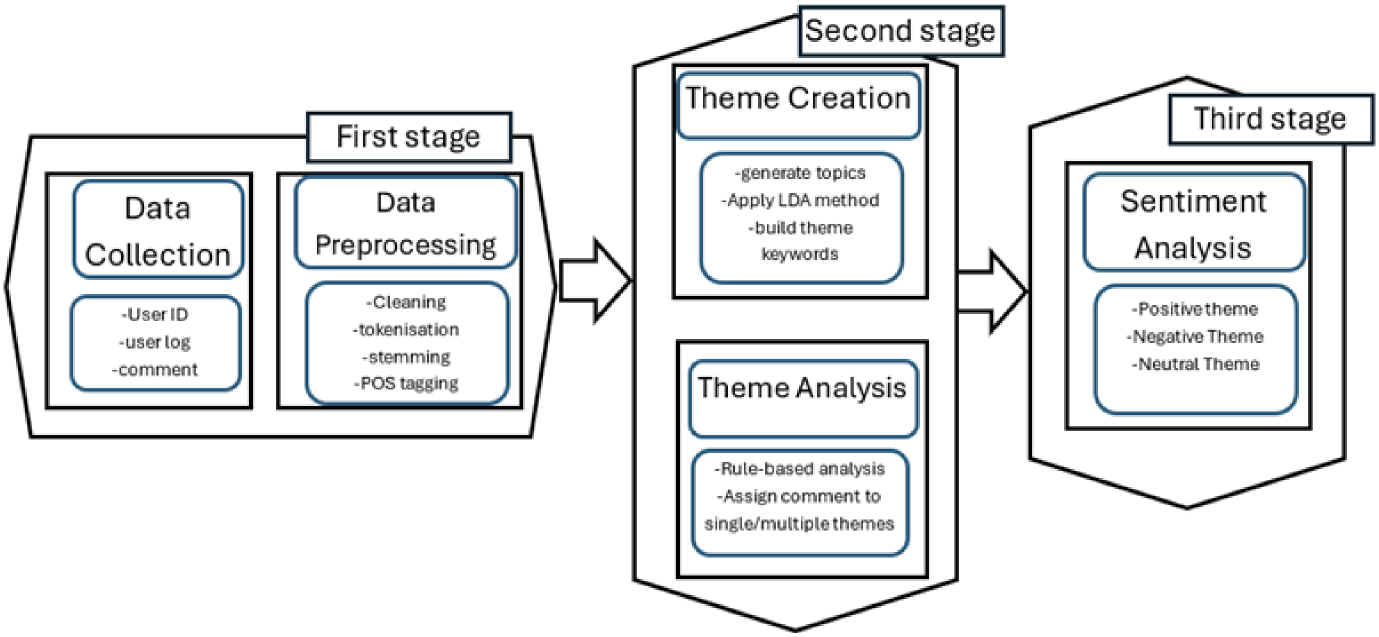

Figure 1: A description of three stages of systematic analysis of comments from users of the contact tracing app

Data Preprocessing

This stage involved cleaning and preparing the comments in the Excel file, which includes: de-identification of each record to protect individuals' privacy by removing or obscuring personally identifiable information from data while still allowing it to be used for analysis. The source file (Excel file) was read and the comment column was renamed to a variable name to identify the column in order to enable referencing during processing. Further, duplicates, spam, and irrelevant comments, which may be a result of erroneous input or incomplete records were removed. The text (lowercase, remove punctuation, special characters, stop words) was normalised with Natural Language Toolkit (NLTK) Python library to ensure all the comments are consistent and remove unwanted characters. Lastly, tokenization and lemmatization/stemming were carried out using NLP and part-of-speech tagging tools from nltk, and nltk. corpus libraries in Python.

Theme Creation

To analyse and categorise user experience comments, we employed an unsupervised natural language processing technique known as Latent Dirichlet Allocation (LDA), a topic modelling technique used to identify hidden themes in text data. This approach enabled the identification of dominant themes in the dataset without relying on predefined labels or categories. The cleaned and tokenised text was used to generate a dictionary and a bag-of-words corpus, which served as input for the LDA model. The model was trained using the Gensim library, with the number of topics empirically set to *n*, balancing interpretability and model coherence.

Each topic was represented by a distribution of keywords, which were manually interpreted and labelled based on the most representative terms. For instance, a topic containing terms such as "easy," "navigation," and "interface" was labelled as "*Ease of Use*" theme. This thematic analysis facilitated the classification of user feedback into distinct experiential categories.

Thematic analysis

Each cleaned comment was analysed against a predefined set of keywords associated with key themes. If any keyword from a theme's list was present in a comment, the comment was assigned to that theme. If a comment matched keywords from multiple themes, the first matching theme in the priority list was assigned. Comments that did not match any of the specified keyword sets were labelled as "Other". This rule-based classification allowed for a rapid, transparent mapping of user feedback into categories relevant for further qualitative and quantitative analysis. A rule-based approach was selected over more complex machine learning or topic modelling techniques for several reasons: it provides transparent decision criteria, which is important when working with stakeholders or interdisciplinary teams who may not be familiar with black-box models. Given the moderate volume of comments, the rule-based method enabled rapid categorisation without the need for model training, labelled data, or parameter tuning.

Sentiment Analysis

In the sentiment analysis performed on the user comments, we utilised the TextBlob library in Python to evaluate the emotional tone of each comment. The analysis generated a polarity score ranging from -1.0 to 1.0, where values closer to -1.0 indicate strong negative sentiment, values near 0.0 suggest neutrality, and values approaching 1.0 reflect strong positive sentiment. Based on these scores, comments were categorised into three sentiment classes: Positive, Neutral, and Negative. This approach allowed us to quantify users' emotional responses to the app and the research experience, providing insights into overall user satisfaction and areas that needed improvement. Additionally, for comments under the "Other" thematic category, this sentiment score helped to further classify them into either "Neutral", "Positive", or "Negative", ensuring even uncategorized feedback contributed to the overall understanding of user experience.

Results

The results of the analysis and evaluation are presented in this section, as well as a data description of the collected users' responses.

Data description

The data comprises one response from 128 participants, well-structured with four main columns, each entry capturing the timestamp, email address, expression of the user's overall experience (feedback), and whether the participant is willing to join similar research in the future. The feedback ranges from brief affirmations such as *"It was easy and direct"* to more detailed comments recognising the app's value in understanding social behaviours, challenges, and the ease of participating in the study. After preprocessing, the number of records was 127 responses.

Four themes were derived from the LDA model, where the number of topics, *n*, was set at 10 to extract topics to determine the themes. Usability, performance, content/feature, engagement/interest were the themes derived from the topics. Table 1 presents the themes and the keywords that describe each theme for rule-based analysis. The Usability theme assesses how easily users interact with the app, measuring efficiency and comfort in achieving their goals. The performance theme refers to the technical reliability and responsiveness of the app. Content/Features theme relates to what the app offers, its tools, modules, design elements, and how those are organised. This helps determine whether the app meets user needs and expectations in terms of functionality and depth. The engagement/Interest theme reflects how captivating and meaningful the experience is for users.

Figures 2 and 3 are two bar charts that present a comparison of how user comments were distributed across thematic categories when assigned to a single theme versus when allowed to be classified under multiple themes.

In Figure 2, which displays the distribution under a single-theme assignment, over half of the comments, 52.8%**,** fell into the "Others" category, suggesting that many responses either were too general for

Table 1: Keywords that describe the themes for analysing users' comments

Theme	Theme Keywords
Usability	navigate, easy, simple, straightforward, intuitive, friendly, seamless, smooth, direct, interface, accessible, clear, effortless, efficient, convenient, fast, onboard
Performance	lag, bug, fast, response, slow, laggy, buggy, crash, sTable, error, loading, freeze, frozen, glitchy, efficient, optimised, perform
Content /Features	access, feature, tool, option, function, content, module, layout, dashboard, custom, interact, accessible, update, integrate, control, search
Engagement / Interest	learn, engage, interest, enjoy, fun, entertain, immerse, interact, addictive, help, reward, excite, motivate, stimulate, educate, inform

precise categorisation or addressed areas outside the predefined themes. The remaining comments were more evenly distributed across the defined themes, with the Content/Features theme receiving 17.6%, suggesting noTable user interest in the material or functionalities discussed. The Usability theme, with 16.0%, highlights concerns or observations about ease of use. The Engagement/Interest theme is 8.0%, and the Performance theme is the least represented with only 5.6%, reflecting fewer remarks on user interaction and system efficiency, respectively. This distribution implies that when limited to one primary theme per comment, many insights may be oversimplified or overlooked.

In contrast, Figure 3, based on multiple-theme assignments, captures a more nuanced view of the feedback. While the "Others" category still dominates with 52.8%, the number of mentions for the Content/Features theme rose to 25.6%, and the Engagement/Interest theme nearly tripled to 23.2%. The Usability theme remains constant at 16.0%, while the Performance theme increases slightly to 7.2%. This broader classification approach reveals that many comments addressed more than one theme, particularly around features and user engagement. The comparison highlights that multi-theme tagging better captures the multidimensional nature of user feedback, offering a richer, more accurate understanding of user experience concerns.

Table 2 shows some examples of users' comments

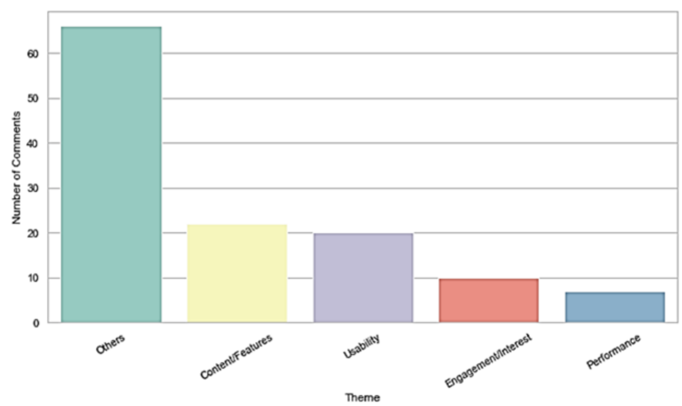

Figure 2: Distribution of comments across thematic categories when assigned to a single theme

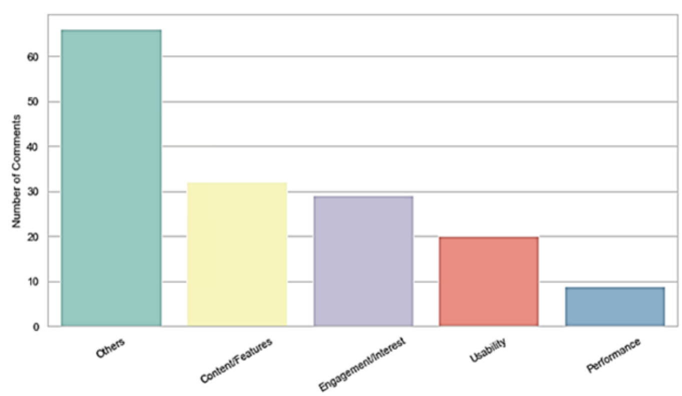

Figure 3: Distribution of comments across thematic categories when assigned to multiple themes

Table 2: Examples of User Feedback Before and After Preprocessing, Categorized by Theme

Comment before preprocessing	Comment after preprocessing	Theme
It was awesome, and easy to know the mobility of people	awesome easy know mobility people	Usability
Noticed even while the app was showing "Tracy is running in the background" it still doesn't affect the performance of the phone.	notice even app show tracy run background still doesn't affect performance phone	Performance
Indeed a great method of exercise a research process, em the only experiences I had is I didn't notice how my data where been taken but I believe that it wasn't having any negative impact on my phone	indeed great method exercise research process em experience didn't notice data take believe wasn't negative impact phone	Content/ Features
It provides more information concerning invisible germs than can be harmful to humans.	provide information concern invisible germ harmful human	Engagement/ Interest
It was good so far	good so far	Others

that are grouped into the corresponding theme. The Table also describes the output of the preprocessed comments, which include removing stop words, converting text to lowercase, removing punctuation, special characters, stop words and lemmatisation.

Thematic Sentiment Analysis

Figure 4 describes the distribution of positive, negative, and neutral sentiments for each theme. The sentiment analysis results highlight a notably positive perception of the usability of the app, with 90% of users expressing favourable views. This suggests that most users found the app intuitive, easy to navigate, and efficient in function. Very few users reported negative experiences (5%), indicating minimal frustration with the user interface or workflow. Similarly, the engagement/interest theme yielded strong results, with 80% positive sentiment and no negative feedback at all. This implies the app was enjoyable and meaningful for users, successfully capturing their attention and motivating continued interaction. Neutral feedback in this area (20%) might reflect users who were engaged but not particularly enthusiastic or expressive in their comments.

Regarding the content/feature theme, 72.7% of feedback was positive, showing that most users appreciated the tools, layout, and available functionalities. However, the 9.1% negative sentiment and a relatively high neutral rate (18.2%) may point to areas where content could be expanded, refined, or made more accessible. For the performance theme, sentiment was less favourable compared to other categories: while 71.4% was positive, indicating general satisfaction with speed and reliability, 14.3% of users expressed dissatisfaction. The remaining neutral feedback could suggest that some users did not focus on or experience noTable performance issues. Overall, while sentiment is largely positive across all dimensions, performance and content/feature represent areas with more room for enhancement. This suggests that improvements in technical stability could boost usability and overall adoption.

Figure 5 describes the distribution of users' responses regarding their willingness to participate in similar future research, categorised by thematic areas,

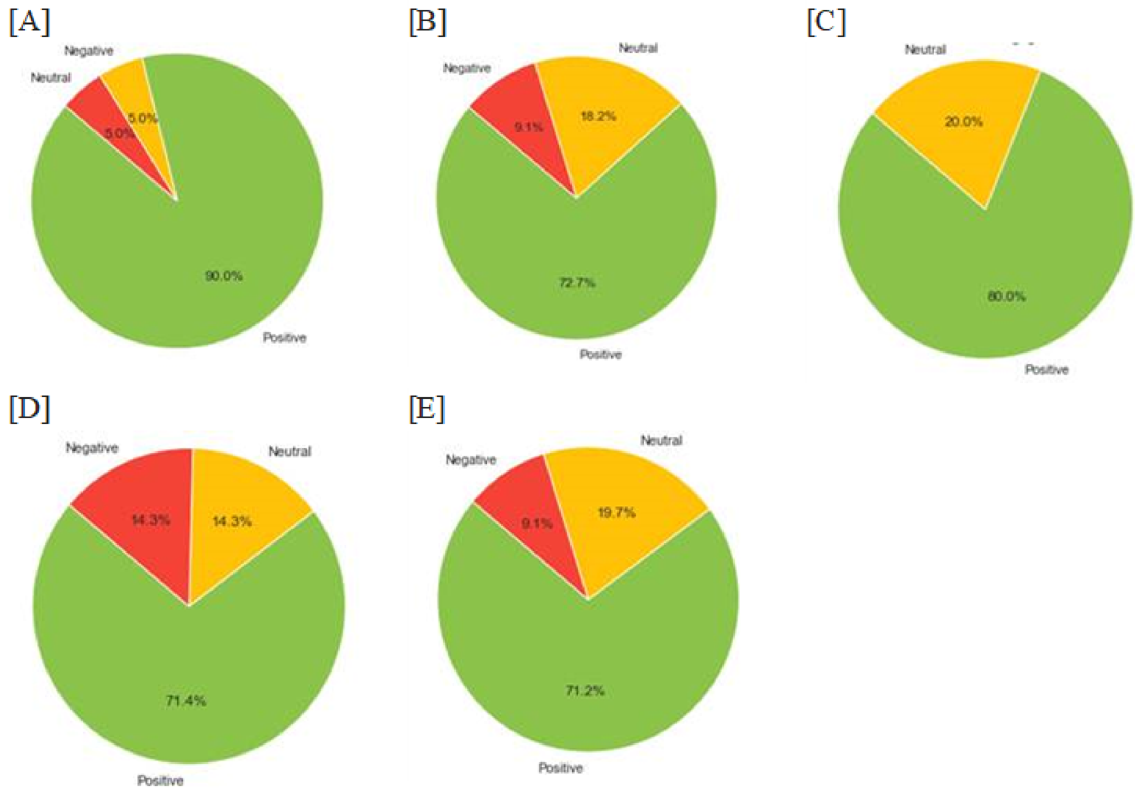

Figure 4: Distribution of sentiment classifications (positive, negative, and neutral) across the thematic categories: [A] Usability, [B] Content/Features, [C] Engagement/Interest, [D] Performance, and [E] Others.

revealing overwhelmingly positive engagement across all themes. Users who commented on Content/Features and Engagement/Interest showed 100% affirmative responses, indicating strong enthusiasm and a high level of satisfaction with the app's functionalities and its ability to capture their interest. Similarly, Usability also had a very high rate of positive responses, with 95% indicating 'Yes', and only 5% responding with 'Maybe', suggesting that users who found the app easy and intuitive to use were also highly inclined to participate in future research.

In contrast, slightly lower levels of commitment were observed among those whose comments focused on "Performance" and "Others" themes. For Performance, 85.7% of users responded 'Yes', while 14.3% expressed uncertainty (Maybe), likely reflecting concerns about technical reliability, such as glitches. Similarly, in the Others category, which includes feedback not directly tied to the main usability themes, 81.8% responded positively, while 18.2% chose 'Maybe', possibly due to more mixed or ambiguous user experiences. Overall, the data indicate that users who had clear, positive experiences, especially in terms of features and engagement, were the most likely to express interest in future participation, whereas those who mentioned broader or technical concerns showed slightly more hesitation.

Discussion

The systematic, scalable approach described in this study successfully analysed user feedback from a mobile contact tracing app, uncovering key themes and sentiments reflecting user experiences. The three-stage process, comprising data preprocessing, thematic extraction using LDA, and sentiment

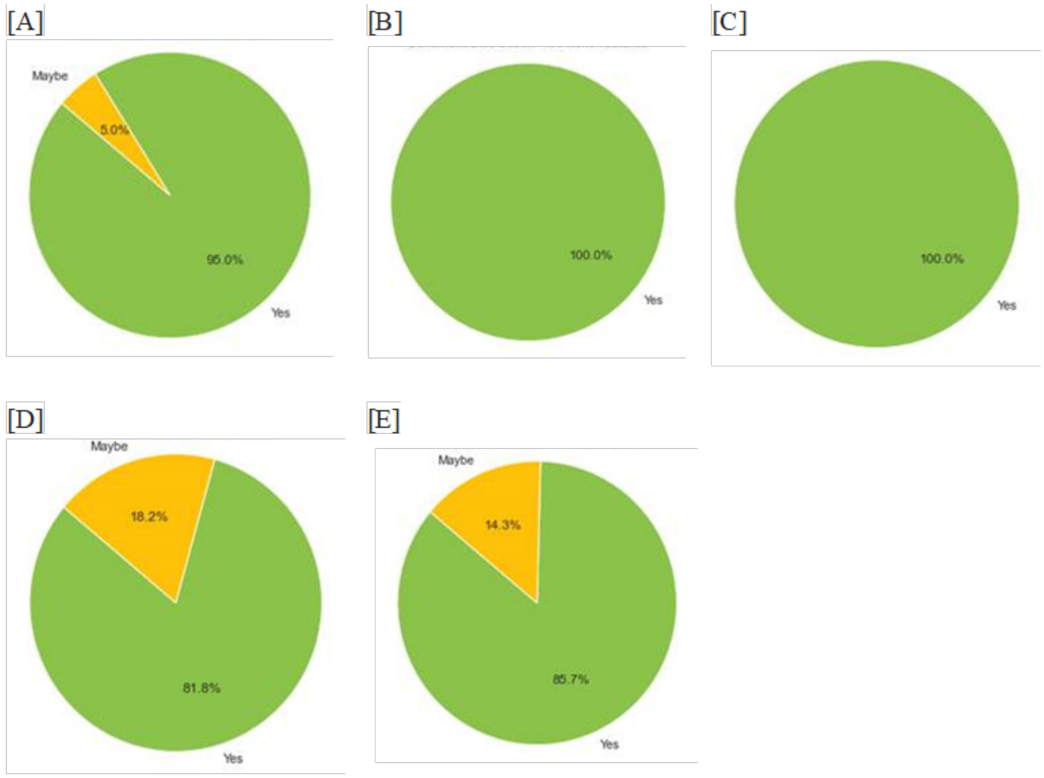

Figure 5: Distribution of users' responses based on their interest in participating in similar research in the future, categorised by the following themes: [A] Usability, [B] Content/Features, [C] Engagement/Interest, [D] Performance, and [E] Others

analysis, enabled a detailed understanding of the themes users focused on and their emotional responses to the app.

The thematic analysis identified four primary areas of user concern and engagement: Usability, Content/Features, Performance, and Engagement/Interest. Sentiment analysis further illuminated user attitudes within these themes, with particularly high levels of satisfaction reported in Usability (90% positive) and Engagement/Interest (80% positive), aligning with findings from Carey *et al*. (2016) and Hu *et al.* (2024), who emphasised that intuitive design and user-friendly interfaces drive adoption. However, Saeidnia et al. (2023) reported lower usability scores in LMICs due to complex interfaces, suggesting the *Tracy* app's success may stem from iterative, context-sensitive design, a gap their study highlighted. Also, Comments under these categories not only praised the app's intuitive design and engaging nature of the app but also correlated strongly with users' willingness to participate in future research,95% and 100%, respectively. This suggests that the app has succeeded in creating a user experience that aligns with best practices in digital public health tools which include simple, appealing, and accessible.

The Content/Features theme also showed a largely positive outlook (72.7%), but the presence of 9.1% negative and 18.2% neutral sentiment suggests that while users appreciated existing features, there is room for improvement in functionality, accessibility, or depth. The Performance category reflected the lowest overall satisfaction, with 14.3% of users expressing negative sentiment, primarily regarding stability, highlighting technical issues that could hinder user trust and continued engagement over time.

However, our usability and Engagement/Interest scores in our study (90% and 80% positive sentiment, respectively) are consistent with universal trends in digital health (Carey *et al*., 2016; Hu *et al.*, 2024), our methodological approach, a three-stage NLP framework for feedback analysis, addresses a critical gap identified in recent literature. While Rödseth *et al.* (2023) highlighted the tension between computational accuracy and interpretability in health intervention app evaluations, our hybrid method (combining rule-based thematic classification with sentiment scoring) offers a scalable and transparent alternative, particularly valuable for public health stakeholders in resource-constrained settings. This builds on Hussein *et al.* (2023)'s call for standardised, actionable feedback tools, while also accommodating the linguistic and thematic diversity observed in open-ended responses, a challenge observed across LMIC-focused studies (Lau *et al.*, 2022; Saeidnia *et al.,* 2023). Previous research in high-income settings, such as Walrave *et al.* (2022), emphasized privacy concerns as a primary barrier to app adoption, Nigerian users in our study prioritized functionality and real-time utility, a divergence that underscores the necessity of culturally and socioeconomically adaptive design in LMICs. This aligns with Musa *et al.* (2024), who similarly identified stability and feature relevance as key drivers in Nigeria, suggesting that digital health strategies must be tailored to local infrastructural and behavioral realities.

Moreover, a significant volume (52.8%) of feedback could not be classified into predefined themes and was grouped under "Others". This suggests that the open-ended feedback format allowed users to submit unstructured comments, leading to vague or off-topic responses (such as, *"It was good so far"*). Without guided prompts, users may not provide actionable insights, resulting in a high volume of unclassifiable data. To improve data quality, future iterations of the app should implement more structured feedback mechanisms, such as: Guided surveys with structured question prompts (such as, *"What features did you find most useful?"*), categorised input fields, dropdown menus or rating scales, which can help collect clearer, more actionable insights from users. For developers, such mechanisms provide clearer pathways for iterative improvements.

To increase the adoption and effectiveness of the contact tracing app, several strategic actions are recommended. First, addressing technical issues, such as improving app stability and optimising performance, should be prioritised to build and maintain user trust. Second, expanding and refining app features in response to user feedback, including adding new tools or enhancing personalisation, can make the app more useful and appealing. Third, given the high levels of user engagement, the app presents a strong opportunity to incorporate public health education and behaviour change messaging to further its impact. Additionally, outreach efforts should also be targeted toward user segments reporting positive experiences, emphasising usability, utility, and the app's contribution to public health to encourage uptake and continued use. Finally, the feedback analysis approach developed in this study should be institutionalised as part of a real-time monitoring system, allowing for agile responses to user concerns and ensuring that the app evolves alongside user needs and expectations.

Conclusion

This study demonstrates the value of applying a structured, data-driven approach to understanding user feedback on a contact tracing app. By integrating thematic analysis with sentiment assessment, we were able to extract meaningful insights about users' experiences, preferences, and challenges. The findings revealed that while users generally responded positively to the app's usability and engagement features, issues related to performance and content refinement still pose barriers to broader adoption and long-term use. The methodology employed, combining rule-based classification, topic modelling, and sentiment scoring, proved effective in capturing both the qualitative richness and emotional tone of user comments. This approach offers a replicable framework that can be applied to other digital health interventions for continuous quality improvement and user-centered design.

Importantly, the analysis provided actionable recommendations to enhance usability and performance of the *Tracy* application, particularly in areas related to system performance, feature enhancement, and user onboarding. Addressing challenges such as Bluetooth connectivity, battery consumption, and clarity of use is essential for strengthening user trust and encouraging long-term engagement. Overall, the study highlights the critical role of usability, technical reliability, and contextual design in ensuring that digital health tools are effective, scalable, and capable of supporting public health initiatives in Nigeria and similar resource-constrained settings.

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