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Original Article

Sentiment Analysis of User Reviews on Medication Reminder Mobile Applications: Insights Into Digital Medication Adherence

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Abstract

Introduction: Non-adherence to medication continues to be one of the most pressing global health problems that has implications for treatment outcomes and patient safety. As mobile health (mHealth) technologies have increased, medication reminder applications have been used more widely to assist people with adherence and self-management. This study aimed to investigate user perception, emotion, and satisfaction with the medication reminder application using a combination of sentiment and thematic analysis of real-world user reviews.

Methods: A mixed method was used, and 4,312 user reviews were obtained from the Apple App Store and Google Play Store. Reviews were pre-processed using natural language processing methods. Moreover, sentiment analysis was conducted using a combination of lexicon-based models, VADER, and TextBlob, as well as the supervised machine-learning model and support vector machine, achieving a 91% accuracy. Finally, thematic analysis was performed using NVivo software to identify repeatable emotional and function-controlled themes.

Results: Among the total reviews, 68.6% expressed positive sentiments, while there were 14.7% neutral and 16.7% negative sentiments. The iOS group had 71.3% positive rating that was slightly higher than that of the Android group (67.2% positive rating). Using thematic analysis, five themes were identified: ease of use, reminder reliability, customization, technical performance, and emotional support. The regression analysis revealed that reliability, user-friendliness of the interface, and durability were the most important factors contributing to positive sentiment (R^2 = 0.61).

Conclusion: In general, users over the counter services to the medication reminder apps, predominantly pointing at usability, reliability, and emotional support as the key factors. The research indicates that the merging of sentiment mining and thematic analysis demonstrates a great potential to unravel user-friendly and emotionally supportive digital adherence tools.

Keywords: Sentiment analysis, Mobile health, Medication adherence

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Introduction

Lack of adherence to medications is one of the most serious challenges in global public health. According to the World Health Organization, nearly 50% of the patients in developed nations do not adhere to their medication schedules.[1,2] However, with this challenge in mind, innovative approaches, such as mobile health, commonly known as mHealth, have been developed with customizable features for reminding and tracking patient medications.[3-5]

The high penetration rate of smartphones with over two billion users worldwide has created a favorable environment for implementing apps related to managing medicines on these devices.[2,6-8] Numerous studies have found thousands of apps related to medicines on prominent platforms, such as Google's App Store and Apple App Store. Ahmed et al, for instance, investigated over 5,800 apps and reported that only a small percentage of them incorporated healthcare professionals in designing apps for medicine management, which have been developed on evidence related to improving patient adherence.[2,5,9-11]

Similarly, Park et al found 704 apps relating to drug adherence and conducted analyses on more than 1,300 reviews, concluding that although consumers valued customizable alerts and multiple profiles, tech problems and sync problems remained issues.[12] This finding highlights the value of user experience and feedback as part of assessing effectiveness for drug adherence apps, irrespective of their tech functionality.[2,12]

User-generated surveys provide a unique and original source of data for understanding public perceptions and satisfaction with mobile health apps.[13-15] Traditional survey research is subject to issues with subjectivity and limited sample sizes, but these issues do not exist with online app reviews, demonstrating both quantity and authenticity.[14,16,17]

Recent research on digital healthcare has utilized increasing levels of sentiment analysis, which is a method in computational linguistics for analyzing the expressivity of emotions in texts, to investigate how these emotional reactions occur with respect to app functions and features.[15,18-20] They include, for instance, investigations by Meyer and Okobojewo involving depression apps on which it was found that users' emotional reactions tended to greatly differ based on app functionality, with negative emotional reactions, such as anxiety, evoked by features involving medical assessments.[15] Moreover, using machine-learning (ML) algorithms on 2,678 reviews by the users of apps for managing diabetes, Osai and Wickramasinghe attained 97% classification accuracy regarding the positive, negative, and neutral sentiments expressed.[18]

These developments have significant implications for both mining sentiments on app reviews for assessing satisfaction levels and obtaining design and engagement strategies for improving apps.[17,19,20] Despite such significant advances in research, literature related to studies on apps for reminding medications is relatively limited. Reviews have reported on app features and strategies for behaviors related to adherence, but a limited body of research is available regarding thorough analyses related to sentiments on various apps across platforms.[2,12,21]

Additionally, current assessments have relied on application descriptions or controlled studies, without considering natural feedback expressed via public application stores.[12,22,23] Considering that overall satisfaction and emotional experiences have a significant effect on application adoption, engagement, and subsequent medicine adherence [15,24-26], it is important to gain a deeper insight into overall sentiments expressed by users. Thus, the current assessment will aim to meet this need by comparing overall sentiments expressed by users about reminder apps selected on Google and Apple App Stores.

Through the combination of quantitative sentiment scoring and thematic analyses, this research seeks to (1) uncover prevalent emotional themes associated with user feedback, (2) draw comparisons between patterns on popular apps, and (3) glean information on improving overall user experience and adherence-related features. In addition, this study contributes to the growing field of digital health informatics by demonstrating how user-generated data can be analyzed to inform the development of more effective and user-centered technologies for medication adherence.

Methods

Research Design

This study used a mixed methods design, employing both quantitative and qualitative techniques for sentiment analysis. The procedure consisted five distinct elements: (1) selecting apps for analysis, (2) extracting data from these apps, (3) performing data preprocessing tasks, (4) classifying and establishing the levels of overall sentiments found within these apps' data sets, and (5) conducting thematic content analysis.

App Selection Criteria

Google Play Store and Apple Store apps for reminding about medications were searched by using several terms, including "medication reminder," "pill tracker," and "medication adherence". The selection criteria were (1) being free and available in English, (2) having more than 100 reviews, (3) having the primary functionality for managing medications and reminding users, and (4) having been last updated in the past two years. Apps that had only fitness-related features or other features were eliminated from the analysis.

These criteria were used to identify five leading apps that could be compared, with both Android and iOS operating systems.

Data Collection

Customer reviews on Android and iOS devices were collected through web scraping using various Python libraries, such as 'BeautifulSoup' and 'Google-Play-Scraper' for Android devices and 'App Store Scraper' for iOS devices, between January 2023 and March 2024. Metadata collected per customer review included the name of the application, rating (1–5 stars), date, and review.

Overall, 5,000 reviews were collected (2,800 from Google Play and 2,200 from Apple App Store). Duplicates, non-English entries, and ads were eliminated via preprocessing, and 4,312 unique reviews remained for analysis.

Data Preprocessing

Data preprocessing was performed under standard natural language processing practices, including tokenization and textual normalization using NLTK and spaCy libraries, stop word and punctuation/emoji stripping, lemmatization for word normalization, and case conversion to lower case. The cleaned corpus was then archived in a structured CSV-formatted database.

Sentiment Analysis

Sentiment classification was performed by combining both lexicon-based and ML models.

Lexicon-Based Approach: Valence Aware Dictionary for sEntiment Reasoning (VADER) and TextBlob algorithms were employed to measure polarity scores between −1 (negative) and + 1 (positive).

Machine-Learning-Based Approach: The supervised models were developed in Python using scikit-learn library on a human-annotated data subset (n = 500) for classification. Logistic regression, support vector machine (SVM), and random forest classification algorithms were utilized as well.

Among the tested models, the SVM classifier achieved the highest performance, with an accuracy of 0.91 and an F1-score of 0.89, and was, therefore,s selected for the final classification. Next, the sentiments were classified into positive, neutral, and negative categories using polarity thresholds.

Thematic Analysis
A thematic analysis was conducted using NVivo 14 software. Themes related to usability and functionality features were analyzed, extracted, and inductively coded by reviewing the corpus of user comments. The themes were verified for intercoder reliability by two distinct researchers, which resulted in a high degree of agreement (Cohen's kappa statistic of 0.86). Key themes are supported with illustrative exemplar quotes.

Data Analysis Tools
All computational analyses were conducted using Python 3.10 and related libraries, such as Pandas, NumPy, NLTK, Sklearn, and Matplotlib. Statistical tests (chi-squared and analysis of variance) were employed to assess any significant differences in the distribution of sentiments across platforms. Moreover, graphs relating to proportion and word frequency plots for sentiments were created using WordCloud and Seaborn, respectively.

Validity, Reliability, and Ethical Issues
All data are publicly accessible via application stores; thus, personal information is not gathered. Secondary data are used following all required protocols for human subjects, following the Declaration of Helsinki (2013).

A mixed cross-validation strategy including lexicon-based and supervised approaches was used to enhance robustness. Additionally, all preprocessing scripts and codes used for analyses were documented.

Results
Overview of the Dataset
In general, 4,312 valid user reviews were collected from five leading medication reminder applications. The distribution of reviews among Google Play Store (n = 2,712; 62.9%) and the Apple App Store (n = 1,600; 37.1%) is presented in Table 1. On average, each review contained 38.6 words (SD = 21.3). The overall mean user rating across all applications was 4.21 out of 5, reflecting generally positive user perceptions.

Sentiment Distribution
Using a hybrid model combining VADER and SVM approaches, these reviews were classified under positive, neutral, and negative categories. The obtained data (Table 2) confirmed that nearly 69% of all consumer feedback was related to positive reviews.

Positive sentiments significantly outweighed negative ones ($\chi^2 = 112.47$, $P < 0.001$). The polarity scores ranged from −0.92 to + 0.96, with a mean polarity of + 0.37 (SD = 0.42), confirming an overall positive tone among users.

Apps with higher ratings (≥ 4.2) demonstrated a greater proportion of positive reviews (above 70%), suggesting a strong correlation between sentiment polarity and numerical app ratings ($r = 0.82$, $P < 0.01$; Figure 1).

Sentiment Variation Across Platforms
Comparative analysis between the Android and iOS platforms revealed slight but statistically significant differences. The prevalence of positive sentiment was slightly higher on iOS (71.3%) compared to Android (67.2%), while negative sentiments were more common among Android platforms (17.9%) compared to iOS platforms (14.2%) (Table 3).

These differences may reflect user interface consistency and technical stability differences between the two ecosystems, as noted in several user comments.

Machine-Learning Model Performance
Among the tested classifiers, SVM demonstrated superior performance compared to logistic regression and random forest. The SVM model achieved the highest accuracy and F1-score (Table 4).

The results confirmed that the SVM classifier provides robust and consistent sentiment classification for short, informal text typical of user reviews.

Thematic Analysis of User Reviews
Thematic analysis of the 4,312 reviews resulted in five main themes and twelve subthemes that portrayed the primary aspects of consumer experiences. In addition, the qualitative analysis led to themes, which are listed

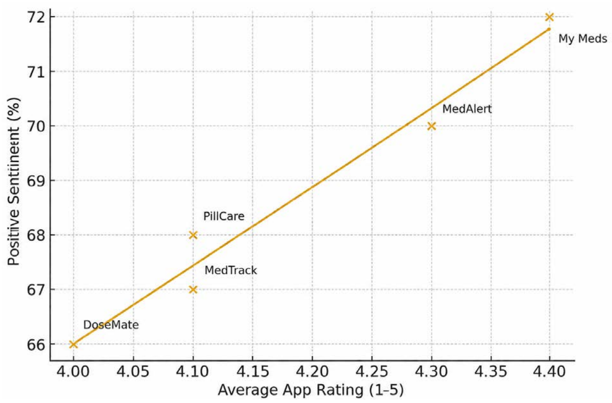

Figure 1. Correlation Between Average App Rating and Positive User Sentiment

Table 1. Overview of Selected Medication Reminder Applications

App Name	Platform	Number of Reviews	Average Rating	Mean Review Length (Words)
MedAlert	Android	1,050	4.3	36.2
PillCare	Android/iOS	900	4.1	41.7
MyMeds	iOS	780	4.4	37.5
DoseMate	Android	820	4.0	35.9
MedTrack	Android/iOS	762	4.1	42.1

in Table 5, with usability and reliability being the most important factors.

The *Ease of Use* (29.4%) and *Technical Performance Issues* (15.2%) were the most prominent positive and negative themes, respectively. Neutral reviews often expressed requests for new features, such as integration with wearable devices or refill reminders.

Correlation Between Sentiment and App Features

A multiple regression analysis revealed that user sentiment was significantly predicted by three feature-related variables: reminder reliability ($\beta = 0.42$, $P < 0.001$), user interface simplicity ($\beta = 0.35$, $P < 0.001$), and technical stability ($\beta = 0.28$, $P < 0.01$). Overall, these predictors explained 61% of the variance in overall sentiment ($R^2 = 0.61$), suggesting that technical performance and usability, rather than visual appeal or novelty, are the strongest drivers of user satisfaction.

Table 2. Sentiment Distribution of User Reviews Across Medication Reminder Apps

Sentiment Category	Frequency	Percentage
Positive	2,956	68.6
Neutral	634	14.7
Negative	722	16.7

Table 3. Comparison of Sentiment Distribution Between Android and iOS Platforms

Platform	Positive (%)	Neutral (%)	Negative (%)
Android	67.2	14.9	17.9
iOS	71.3	14.5	14.2

Keyword Frequency and Emotional Polarity

Figure 2 illustrates a word cloud of the most frequently used terms in user reviews, where word size reflects usage frequency. The top 15 most frequently utilized words across reviews were "*reminder*," "*easy*," "*helpful*," "*alarm*," "*crash*," "*dose*," "*update*," and "*notification*." Furthermore, words associated with positive sentiment included "*useful*," "*life-saver*," "*helpful*," "*simple*," and "*consistent*." Moreover, negative sentiment keywords were dominated by "*crash*," "*bug*," "*missed*," and "*doesn't work*." The emotional polarity distribution further confirmed that functional reliability

Table 4. Performance Metrics of Tested Machine-Learning Models for Sentiment Classification

Model	Accuracy	Precision	Recall	F1-Score
Logistic regression	0.87	0.85	0.84	0.84
Random forest	0.88	0.86	0.86	0.87
SVM (final model)	0.91	0.90	0.89	0.89

Note. SVM: Support vector machine.

Table 5. Main Themes, Subthemes, and Representative User Quotes From Thematic Analysis

Main Theme	Subthemes	Frequency (%)	Representative User Quote
Ease of use and interface design	Simple navigation and intuitive layout	29.4	"I love how easy it is to add new meds and set reminders—it takes seconds."
Reminder accuracy and reliability	Notification timing, and missed alerts	22.1	"Sometimes the alarm doesn't go off, and I miss doses."
Customization and flexibility	Sound options, dosage frequency, and scheduling	17.6	"Being able to set custom reminders for each pill really helps."
Technical performance and bugs	Crashes, sync errors, and battery drain	15.2	"App freezes after last update—frustrating when I rely on it daily."
Emotional impact and motivation	Anxiety reduction, feeling supported, and trust	15.7	"This app makes me feel more in control of my treatment."

Figure 2. Word Cloud Visualization of the Most Frequent Terms in User Reviews
Note. Larger words indicate higher frequency

directly shaped emotional tone.

Summary of Key Findings

- Over two-thirds (68.6%) of user feedback expressed positive sentiments.
- Reliability and ease of use were the strongest positive determinants of satisfaction.
- Technical glitches and synchronization errors were the dominant negative triggers.
- iOS users reported marginally higher satisfaction than Android users.
- ML (SVM) achieved high accuracy (91%) in classifying sentiments.
- Thematic analysis identified "ease of use," "reminder reliability," and "emotional support" as the top three user-valued attributes.

Collectively, these findings highlight that user satisfaction with medication reminder apps depends more on functional reliability and user-centered design than on aesthetic or advanced technological features.

Discussion

The outcomes of this study offer detailed understanding of users' perceptions, opinions, and emotional responses toward medication reminder mobile applications. The use of sentiment analysis combined with thematic analysis indicated that, overall, users had a positive sentiment toward medication reminder applications, with 68.6% of reviews indicating their satisfaction. This finding conform to the findings of previous works, demonstrating that mobile health apps, in particular those aimed to help with adherence, are positively viewed by users when they are effective, simple to use, and helpful with everyday medication use.[2,26,27]

Moreover, our findings corroborate those of Park et al, reporting that customizable reminders, flexible scheduling, and user-friendly interfaces are the most appreciated features in adherence apps.[12] Similarly, Tabi et al and Al-Arkee et al observed that usability and design simplicity are strong determinants of positive app evaluations and long-term engagement. In our dataset, the themes "ease of use" (29.4%) and "reminder reliability" (22.1%) were the most frequent positive aspects, mirroring user expectations identified in these earlier works.[21,28]

Furthermore, the slight difference in sentiment distribution between iOS and Android users, higher positivity among iOS users, echoes the observations of Santo et al, highlighting that differences in operating system consistency and update frequency can influence perceived app quality.[27] iOS apps typically demonstrate better synchronization and fewer performance glitches, which may explain the higher satisfaction rates found in our study.

Our results also reinforce the conclusions of Ossai and Wickramasinghe, demonstrating that the sentiment mining of user reviews can accurately identify key satisfaction drivers in chronic disease management apps.[18] The strong predictive relationship between reminder reliability, interface simplicity, and user sentiment in our regression model ($R^2 = 0.61$) supports the notion that technical performance and usability are the core components of perceived app quality.

On the other hand, technical instability, synchronization errors, and crashes were the main contributing factors to negative sentiment, which corroborates the findings of studies performed by Ahmed et al and Bailey et al, revealing that poor interoperability and software malfunction can undermine user trust and adherence continuity considerably.[2,4] In particular, since adherence interventions are digital, they rely on repeated use for sustained time periods, so even minor performance issues can limit effectiveness and user retention.

A novel contribution of this study is the identification of the emotional dimension of user experience in medication adherence apps. Beyond technical and usability factors, approximately 15.7% of reviews described emotional impacts, such as anxiety reduction, reassurance, or increased sense of control, which aligns with the results of Meyer and Okuboyejo, indicating that emotional reactions, particularly positive affect and perceived support, enhance user engagement and mental well-being in digital health contexts.[15]

Our findings emphasized that people appreciate medication reminder apps when they create motivation and provide psychological safety. The double role, functional-supportive and affective, confirmed that the future designs of adherence apps should implement behavioral support strategies designed to reinforce both adherence and emotional safety, such as providing motivational feedback, empathic language in the interface, and visual indications of progress.

The application of ML-based sentiment analysis in this study provided a robust and scalable alternative to traditional user surveys, which are often constrained by limited sample sizes and self-report bias. Our hybrid model combining lexicon-based (VADER/TextBlob) and supervised (SVM) approaches achieved 91% accuracy, which is consistent with the performance range reported by Ossai and Wickramasinghe and Samanmali and Rupasingha.[18,20] These results validate the effectiveness of artificial intelligence techniques in extracting reliable user experience metrics from large, unstructured text data.

Moreover, our thematic coding confirmed high inter-coder reliability ($\kappa = 0.86$), indicating methodological rigor in qualitative interpretation. Thus, integrating computational and interpretive techniques provides a more holistic understanding of user experience, thereby bridging the gap between quantitative metrics (ratings and sentiment scores) and qualitative insights (perceived value and emotional impact).

From a practical standpoint, the results emphasized that app developers and healthcare providers should prioritize functional reliability, intuitive design, and emotional engagement when developing or recommending medication reminder apps. In addition, the presence of frequent software crashes, delayed notifications, or synchronization issues, although seemingly technical, can directly reduce adherence rates by eroding user confidence.

Consistent with the results of Ahmed et al and Al-Arkee et al, our findings underscore the necessity of healthcare professional involvement in app development to ensure clinical accuracy, safety, and credibility.[2,28] Only a small number of adherence apps, which were examined in earlier research, showed collaboration, which is one reason that there is still a considerable difference in quality among the platforms. Multidisciplinary teams, consisting of doctors, behavioral scientists, and user experience designers, can apply their expertise to improve the functional and psychological usability of the new technologies aimed at increasing adherence.

Moreover, the emotional feedback detected in this research indicates that there are ways to incorporate affective computing and persuasive design elements (e.g., motivational messages that are tailored to the individual and visual progress tracking). These functionalities can have a positive impact on the user's motivation, especially on the patients with chronic diseases being the major target group that needs support for adherence over long periods.

Limitations and Future Implications

While this study contributed to the body of literature in sentiment analysis related to health apps, it had several limitations. Similar to the other studies of sentiment analysis, text analysis is limited by the ambiguity of language and the lack of contextual information in short text reviews. In addition, the data were restricted to reviews available from public app stores, which were utilized for the reported analysis. Therefore, additional user characteristics were not assessed in the reviews; this research may not be representative of the overall user demographic, especially among older adults and those with lower digital literacy. Furthermore, while the hybrid sentiment model performed well, future studies may wish to explore deep-learning architectures to model and analyze additional complex semantic patterns. Future studies would benefit from exploring sentiment and user expectations in a multi-cultural context, as a region's healthcare systems and endowed digital literacy can impact app expectations. Future studies may consider following sentiment over time to find if and how other features, updates, and the like influence user satisfaction.

Conclusion

Overall, this research added to the field of digital health research by clearly demonstrating that users have a mostly positive sentiment toward medication reminder apps, stemming mainly from reliability, usability, and perceived emotional support. By combining sentiment analysis with thematic analysis, our study provided both methodological advancement and practical insights for the next generation of adherence-supporting technologies. Technical stability, user-centered design, and emotional impact are key contributors to the eventual sustained effectiveness of mHealth solutions to improve medication adherence and subsequently improve patient outcomes.

Authors' Contribution

Conceptualization: Zeinab Valizadeh, Amin Pourali
Data Curation: Zeinab Valizadeh, Amin Pourali
Formal Analysis: Amin Pourali
Investigation: Zeinab Valizadeh
Methodology: Amin Pourali
Project Administration: Amin Pourali
Resources: Zeinab Valizadeh, Amin Pourali
Software: Zeinab Valizadeh
Supervision: Zeinab Valizadeh
Validation: Amin Pourali
Visualization: Zeinab Valizadeh
Writing–Original Draft: Amin Pourali
Writing–Review & Editing: Amin Pourali

Availability of Data and Materials

The datasets generated and analyzed during this study entirely consist of publicly available user reviews, which can be directly accessed from the listing pages of the relevant applications on the Google Play Store and Apple App Store. No primary datasets were generated by the authors.

Competing Interests

The authors of this study declare they have no personal, professional, or financial conflict of interests.

Consent for Publication

Not applicable.

Ethical Approval

All methods were performed in accordance with relevant guidelines and regulations for research involving user-generated data. In addition, all reviews were anonymized prior to analysis.

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Intelligence Use Disclosure

The authors used Grok to receive grammar recommendations in order to improve manuscript readability. All artificial intelligence-generated language suggestions were reviewed and edited by the authors.

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