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Leveraging Sentiment Analysis to Optimize Customer Experience in Digital Wallets: A Case of Opay Wallet

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ABSTRACT
With the growing adoption of digital financial services, customer experience has become a key differentiator for fintech companies. Sentiment analysis offers a data-driven approach to understanding user opinions, enabling companies to improve service quality and address customer concerns proactively. This study leverages sentiment analysis to assess user feedback on the Opay Wallet, a leading mobile payment platform. Using a dataset of user reviews collected from the Google Play Store between September 2018 and December 2024, TextBlob was employed to classify sentiments as positive, neutral, or negative. The results indicate that 82.2% of reviews were positive, 13.5% were neutral, and 5.5% were negative, suggesting an overall favorable perception of Opay Wallet. Furthermore, Latent Dirichlet Allocation (LDA) topic modeling was applied to identify key themes in user feedback. The analysis revealed that users frequently praised transaction speed, ease of use, and reliability, while negative reviews highlighted concerns about customer support and occasional transaction failures. These insights underscore the importance of optimizing fintech services based on real-time user sentiment. The study recommends continuous sentiment monitoring and AI-driven customer support enhancements to maintain user satisfaction and competitive advantage in the digital payments industry.

Keywords:
Sentiment Analysis,
Opay Wallet,
Fintech,
Customer Experience,
Natural Language Processing (NLP).

INTRODUCTION

Digital wallets have transformed the global financial ecosystem, providing convenient, secure, and inclusive ways to manage transactions in both developed and developing economies. As technology continues to evolve, so do the expectations of consumers who demand seamless and user-friendly experiences. In this context, digital payment solutions have emerged as indispensable tools for individuals and businesses alike.
In Nigeria, where financial inclusion is a pressing challenge, digital wallets such as Opay Wallet have risen to prominence, bridging gaps in traditional banking systems and offering accessible financial services to a diverse population (Uchenna et al, 2024).
Opay Wallet, a product of the Opera Group, has become a household name in Nigeria's fintech landscape. The platform allows users to perform a wide range of financial activities, including money transfers, bill payments, airtime purchases, and even ride-hailing services. By integrating multiple functionalities into a single platform, Opay aims to address the financial needs of both the banked and unbanked populations (Effiom and Edet, 2020). However, the success of any digital wallet depends not only on its features but also on the quality of the customer experience it delivers. As competition within the fintech space intensifies, optimizing customer satisfaction becomes a strategic priority.
Customer experience is a multifaceted construct that encompasses every touchpoint a user has with a product or service. It includes usability, reliability, responsiveness, and emotional engagement (Bouaddi et al, 2024). For digital wallets, these dimensions are even more critical as they directly affect the trust and loyalty of users who rely on these platforms for essential financial transactions. Understanding how customers perceive and interact with a digital wallet is key to refining its services and ensuring sustained user engagement. This is where sentiment analysis emerges as a powerful tool.
Sentiment analysis, also known as opinion mining, is a technique in natural language processing (NLP) that involves the extraction and classification of subjective information from textual data. It allows businesses to

analyze customer feedback, reviews, and social media discussions to gauge public opinion about their products or services. By applying sentiment analysis to Opay Wallet, this study seeks to uncover the emotions, attitudes, and opinions expressed by users, offering valuable insights into the factors that enhance or detract from their experience.

The application of sentiment analysis in understanding consumer behavior has gained considerable traction in various industries, including retail, tourism, and financial services. Sentiment analysis, which involves the use of natural language processing (NLP) to detect and extract subjective information from textual data, allows businesses to assess customer opinions, emotions, and attitudes (Pang and Lee, 2008). Within the context of digital wallets, sentiment analysis offers a powerful tool for gauging customer satisfaction and dissatisfaction, which can guide companies in optimizing their services. Research shows that sentiment analysis helps businesses monitor customer feedback, identify emerging trends, and improve their products and services (Liu, 2012). For fintech companies like Opay Wallet, understanding customer sentiment is essential to enhance user experience and foster greater engagement.

The authors of a research by Maindola et al. (2018) try to examine the opinions of Indian users of digital wallets about various payment apps. The authors use IBM Watson software tools to analyze sentiment across many social networks while accounting for varied payment systems. From November 8, 2016, to November 7, 2017, the authors examined documents, forums, tweets, and other venues where users provided comments on the wallets. This study offers a number of intriguing insights regarding user sentiments and India's willingness to embrace digital payment options. A study conducted by Deviani et al. (2022) assessed user sentiment on the quality of Dana and ShopeePay services using the e-servqual dimensions and identified the subjects associated with each dimension to evaluate the service quality of both platforms. The data sources for the research were Dana and ShopeePay user-generated content delivered through social media Twitter. The data retrieval technique was crawling user tweets containing the keywords "@danawallet" and "@ShopeePay_ID" with a time span of 23 October 2021 to 29 December 2021. The data obtained was classified based on the e-servqual dimension using Naive Bayes and the dataset will be analyzed using sentiment analysis and topic modeling. The findings of this study indicated that negative feelings prevail in the e-servqual assessments of Dana and ShopeePay across the dimensions of Efficiency, System Availability, Fulfillment, and Privacy, with subjects and terminology with unfavorable connotations for the services offered by Dana and ShopeePay.The results of this research can be used by Dana and ShopeePay as an evaluation of service quality, especially on the e-servqual dimension to increase user satisfaction to maintain user loyalty and improve user perceptions.

A research conducted by (Zahra and Alamsyah, 2022) sought to identify critical future enhancements for digital wallet applications through user evaluations, including multiclass classification and sentiment analysis. The study applied the Naïve Bayes classification by first preprocessing 53,968 user reviews and labeling them into seven electronic service quality dimensions: efficiency, responsiveness, fulfillment, system availability, contact, privacy, and compensation. The result achieved an accuracy of 0.784 with a dataset of 11,885 user reviews. Furthermore, the sentiment analysis against the seven dimensions identifies more than 69% positive sentiments in all dimensions, except the compensation dimension approaching less than 42%, implying that the dominating digital wallet issue resides in the customer's compensation problem. The study concluded that Naïve Bayes classification and sentiment analysis contributed positively to the quality of digital wallet services. Similarly, (Renaldi, 2023) did study on non-standard terms such as slang and word abbreviations. The study included 3878 tweets, including 70% training data and 30% test data. According to the sentiment analysis conducted in this study, Twitter users in Indonesia are more inclined to remark negatively about electronic wallets. The findings of this study showed that by combining both approaches, adding standard word corrections, and testing using RapidMiner, the accuracy rate for categorizing positive and negative attitudes reached 88.56%. Further study can use Levenshtein Distance normalization in the classification findings to improve accuracy values.

A study conducted by (Harnadi and Widiantoro, 2023) sought to assess the efficacy and precision of supervised learning models applied to sentiment analysis of e-wallets. User comment data was acquired through web scraping from four prominent e-wallet applications in Indonesia: Ovo, Dana, Doku, and LinkAja. The data collection occurred between January and May 2023, resulting in a preprocessed dataset comprising 11,267 entries, with 6,349 labeled as negative and 4,918 as positive. Data labeling employed a star rating system determined by users, where 1-3 stars were classified as negative and 4-5 stars as positive. The labeling outcomes were evaluated using supervised learning models, including Support Vector Machine (SVM), Multinomial Naive Bayes, Bagging with Multinomial Naive Bayes, and Random Forest algorithms. The efficacy of these algorithms is assessed by Precision, Recall, F1-Score, and Support. The accuracy of the algorithms is also evaluated using train accuracy score, test accuracy score, train ROC-AUC Score, test ROC-

AUC score, area under precision-recall curve, and area under ROC-AUC. This study shows that labeling generates a significant value, which means that the user's negative and positive comments need to be considered by the E-wallet manager in order to improve the quality of the system and services.

In another work (Helmayanti et al., 2023), aspect-based sentiment analysis was performed on Flip user evaluations using the naïve bayes algorithm. The test findings are quite accurate, with an average of 0.84. The naive bayes algorithm performs well in identifying user evaluations based on speed, security, and cost, with accuracies of 0.80, 0.87, and 0.84. This study gives valuable information for service providers seeking to increase service performance and innovation. The labeling data produced the greatest sentiment 0 (no sentiment), followed by sentiment 1 (positive) and sentiment 2 (negative). Negative attitudes are more prevalent on speed and security issues, whilst good sentiments are more common on cost issues. To maximize user satisfaction in these areas, changes to the Flip application's security and performance are required. The naive bayes method can be beneficial for analyzing review data from e-wallet applications and other similar services.

To gain a better understanding of user reviews of UPI applications and provide valuable data for the strategic enhancements of these digital platforms, a comparative analysis of various algorithms was carried out by (Jaluthria et al., 2024). Preprocessing is done on datasets, including text transformation using techniques like Word2Vec and Bag of Words, which turn raw text into numerical vectors used by machine learning algorithms; reviews are classified into positive and negative sentiments using sentiment analysis algorithms; and algorithms like C 4.5 (J48), Naive Bayes, and LSTM are used for sentiment classification. Comparative analysis was used to evaluate their efficacy. The greatest accuracy ever reported for sentiment categorization of user reviews on Paytm was 90.02%. This prediction was achieved by using LSTM with the word2vec skip-gram training model. The findings offer insights into user attitudes, enabling deliberate improvements in UPI applications that increase user satisfaction and comply with evolving digital payment standards. The aim of another study by Widianto et al. (2024) was to examine the tone of evaluations of the digital wallet apps Shopeepay, Gopay, and OVO on the Google Play Store. The Knowledge Data Dictionary (KDD) approach, which employed the Naïve Bayes Classifier algorithm, was the study methodology. The Python programming language and Jupiter Notebook are the instruments utilized to assist the study process. Three digital wallet apps—Gopay, Shopeepay, and OVO—were the subject of the study. The Shopeepay application has an accuracy rating of 88% after testing using the Naïve Bayes Classifier algorithm, followed by the OVO application at 86% and the Gopay application at 82%. Based on these accuracy findings, it was determined that the Shopeepay application was successfully analyzed using the Naïve Bayes Classifier method.

MATERIALS AND METHODS

This study applies sentiment analysis to user feedback on Opay Wallet in order to optimize the customer experience by identifying prevailing user sentiments and uncovering actionable insights. The study follows a structured, quantitative approach with a focus on analyzing textual data from customer reviews and feedback related to Opay Wallet. The methodology depicted in Figure 1 outlines the process of data collection, data preprocessing, sentiment analysis, and the analytical techniques used to derive conclusions from the data.

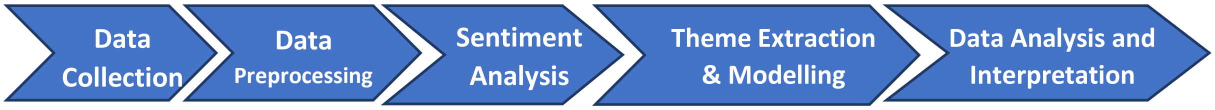

Figure 1: Study Implementation Steps

Data Collection

The data for this study was sourced from publicly available user reviews and feedback on the Google Play Store. This platform was chosen due to its vast repository of user-generated reviews, providing diverse insights into user experiences and sentiments about the Opay Wallet application. The dataset includes reviews from September 2018 to December 2024, ensuring a comprehensive representation of user sentiments over seven years.

To achieve a balanced dataset, the study incorporated reviews with positive, negative, and neutral sentiments. This approach ensures a holistic understanding of user experiences, including both commendations and criticisms. Positive reviews highlight strengths and user satisfaction, while negative reviews shed light on pain points and areas requiring improvement. Neutral feedback, often representing constructive suggestions or lukewarm experiences, adds depth to the analysis by identifying potential enhancements to the platform.

The extended timeframe of the data collection allows for the identification of trends in user sentiment over the years, including shifts in customer perception, the impact of app updates, and responses to new features introduced by Opay. By analyzing this dataset, the study captures both historical and recent user experiences, enabling actionable insights to guide the optimization of the Opay Wallet. The extracted data contains 11 columns as captured in Table 1 but for the sake of this study, only the content column was used for the analysis.

Table 1: Extracted Dataset Attributes

Column Name	Attribute
reviewId	object
userName	object
userImage	object
content	object
score	int64
thumbsUpCount	int64
reviewCreatedVersion	object
at	object
replyContent	object
repliedAt	object
appVersion	object

Data Preprocessing

Effective sentiment analysis begins with thorough data preprocessing to ensure the quality and consistency of the text data being analyzed. For this study, several preprocessing techniques were applied to prepare the user feedback data for sentiment analysis using TextBlob. These techniques are critical for minimizing noise and optimizing the accuracy of the analysis (Manning et al., 2008).

Text Normalization

Text normalization was performed to standardize the input data by converting all text to lowercase. This step ensures that words are treated uniformly, eliminating variations caused by capitalization (e.g., "Good" and "good"). Additionally, special characters, punctuation, numbers, and irrelevant symbols were removed to focus exclusively on meaningful text content. This was done using the RegexpTokenizer library in Python.

Stopword Removal

Stopwords—commonly used words like "and," "the," and "is"—were removed as they do not contribute significantly to sentiment analysis. This process helps to reduce the dimensionality of the text data while retaining the core meaning of the reviews (Bird et al., 2009).

Tokenization

Tokenization involves splitting the text into individual components, such as words or sentences. This step enables TextBlob to process and analyze each unit of text independently, making it easier to compute sentiment polarity and subjectivity scores (Manning et al., 2008). This was done using the RegexpTokenizer library in Python.

Lemmatization

Lemmatization was applied to reduce words to their base or root forms (e.g., "running" becomes "run"). Unlike stemming, lemmatization considers the context of the word, ensuring accurate transformations and enhancing the overall quality of sentiment classification (Jurafsky & Martin, 2020). The WordNetLemmatizer library was used for this task.

Noise Removal and Domain-Specific Terms

Irrelevant or noisy data, such as URLs, HTML tags, and emojis, were removed from the dataset to prevent them from skewing the sentiment analysis. Furthermore, domain-specific terms related to financial transactions and digital wallets were identified and retained, as they contribute to understanding the sentiment context of the reviews. This was done using the re library.

Handling Missing or Duplicate Data

Reviews with missing or incomplete information were removed to maintain the dataset’s integrity. Duplicate entries were also eliminated to avoid bias in the analysis.

Sentiment Analysis

To evaluate user feedback on the Opay Wallet, sentiment analysis was conducted using TextBlob, a Python-based natural language processing library that provides tools for text processing and sentiment analysis. TextBlob was chosen for its simplicity, reliability, and capability to analyze text data and

determine the overall sentiment polarity and subjectivity.
TextBlob performs sentiment analysis by calculating a polarity score and a subjectivity score for each text input:

Polarity Score
This metric ranges from -1 (completely negative) to +1 (completely positive). A score of 0 indicates a neutral sentiment.

Subjectivity Score
This metric ranges from 0 (completely objective) to 1 (completely subjective), reflecting the degree of personal opinion or factual information in the text.
The analysis involved several preprocessing steps to ensure the accuracy of sentiment classification, including text normalization (removing special characters and converting text to lowercase) and tokenization. Each user review was then processed through TextBlob's sentiment analyzer to extract polarity scores. Based on these scores, reviews were categorized into three sentiment classes:

i. Positive: Reviews with polarity scores greater than 0.
ii. Neutral: Reviews with polarity scores equal to 0.
iii. Negative: Reviews with polarity scores less than 0.

TextBlob's strength lies in its reliance on a pre-trained lexicon to assess sentiment. It identifies sentiment-bearing words within the text and evaluates their contribution to the overall polarity. While its lexicon-based approach works effectively in many cases, it has limitations in understanding complex contexts, sarcasm, and domain-specific terminology.
The results from TextBlob provided a quantitative breakdown of user sentiment, enabling the study to identify trends in user satisfaction and areas requiring improvement. These insights formed the basis for further thematic analysis and actionable recommendations for enhancing the Opay Wallet user experience.

Theme Extraction and Topic Modeling
Beyond basic sentiment classification, the study also aimed to extract underlying themes and topics from the user reviews to better understand what aspects of the Opay Wallet platform influenced user sentiment. To achieve this, topic modeling was employed using Latent Dirichlet Allocation (LDA), a popular unsupervised machine learning technique for discovering hidden topics in large text datasets (Blei et al., 2003). The LDA model was applied to the cleaned reviews to identify common themes and topics that emerged across user feedback. These themes were then manually reviewed and categorized to provide further insight into specific user concerns or praises, such as issues with transaction speed, security concerns, customer service experiences, or satisfaction with app features.

Data Analysis and Interpretation
Once the sentiment classification and theme extraction were completed, the results were analyzed to identify patterns in user sentiment and feedback. The analysis focused on the following key questions: What are the most common positive and negative sentiments expressed by users? What themes emerge from the user feedback, and how do they relate to user satisfaction? Are there specific areas of the Opay Wallet platform (e.g., transaction processing, security, customer service) that generate the most negative or positive feedback? The results were then interpreted to provide actionable insights that could inform Opay Wallet's strategy for improving its customer experience. These insights were categorized into specific recommendations for platform enhancements, such as addressing security concerns, improving transaction speeds, or enhancing customer support features.

Limitations
While the methodology was designed to provide valuable insights, there are some limitations to the study. First, the reliance on user reviews from public platforms may not fully capture the opinions of all Opay Wallet users, as some users may not leave feedback. Additionally, the sentiment analysis models may struggle with certain linguistic challenges, such as sarcasm, ambiguous statements, or region-specific expressions, which could affect the accuracy of sentiment classification. To mitigate this, the study used advanced sentiment analysis techniques and linguistic preprocessing, but some subjectivity in user reviews may remain unaccounted for. Finally, while the data collection period provided recent feedback, sentiment can fluctuate over time, and future studies could benefit from longitudinal analysis to capture these changes more comprehensively.

RESULTS AND DISCUSSION
The results of this study provide a detailed analysis of user sentiment and thematic insights derived from Opay Wallet user reviews collected from the Google Play Store. The sentiment analysis, conducted using TextBlob, reveals the overall distribution of positive, neutral, and negative sentiments within the dataset. Additionally, topic modeling through Latent Dirichlet Allocation (LDA) identifies key themes and prominent keywords from the reviews, offering deeper insights into user perceptions and concerns. The result obtained is summarized in Table 2.

Table 2: Result Obtained from Analysis

Overall Sentiment	**count**
Positive	132244
Neutral	21782
Negative	8864

The histogram in Figure 2 illustrates the distribution of user sentiments toward the Opay Wallet. The data shows a clear dominance of Positive reviews (132,244), followed by Neutral reviews (21,782) and Negative reviews (8,864). This visualization emphasizes the overall positive user perception of the wallet.

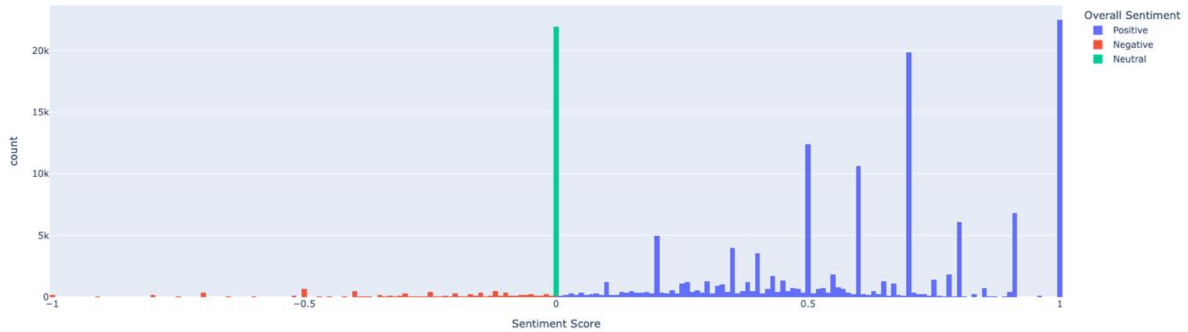

Figure 2: Histogram Showing Results obtained from TextBlob Analysis

The WordCloud in Figure 3 is used to visualize the most frequent and relevant keywords identified through the LDA topic modeling. Words such as “good”, “best”, “app,” "nice," and "opay" prominently feature, indicating key themes of user feedback. Larger words signify higher relevance in the dataset.

Figure 3: WordCloud Indicating the most common words

The visualization of LDA topics and their corresponding keywords in Figure 4 provides a structured overview of the main themes extracted from user reviews. Keywords like "best" and "exceptional" dominate, reinforcing the app's reputation for quality and reliability.

```
[(0,
  '0.231*"best" + 0.084*"one" + 0.078*"the" + 0.061*"app" + '
  '0.042*"exceptional" + 0.025*"application" + 0.025*"ever" + 0.025*"wow" + '
  '0.021*"banking" + 0.017*"opay"'),
 (1,
  '0.182*"ok" + 0.125*"okay" + 0.053*"it" + 0.038*"fine" + 0.030*"splendid" + '
  '0.027*"satisfied" + 0.026*"happy" + 0.026*"too" + 0.024*"is" + 0.018*"am"'),
 (2,
  '0.045*"fair" + 0.030*"satisfying" + 0.019*"wa" + 0.015*"real" + 0.014*"for" '
  '+ 0.013*"and" + 0.012*"now" + 0.011*"pay" + 0.009*"time" + 0.008*"sha"'),
 (3,
  '0.083*"bad" + 0.067*"not" + 0.061*"network" + 0.054*"perfectly" + '
  '0.036*"working" + 0.030*"up" + 0.026*"always" + 0.019*"it" + 0.018*"slow" + '
  '0.012*"update"'),
 (4,
  '0.166*"service" + 0.035*"poor" + 0.030*"no" + 0.018*"opay" + 0.012*"have" + '
  '0.010*"da" + 0.010*"and" + 0.009*"never" + 0.008*"quick" + 0.008*"sunday"'),
 (5,
  '0.588*"good" + 0.193*"very" + 0.053*"cool" + 0.021*"reliable" + 0.021*"so" '
  '+ 0.017*"fast" + 0.008*"it" + 0.007*"sweet" + 0.007*"is" + 0.007*"easy"'),
 (6,
  '0.068*"opay" + 0.050*"my" + 0.045*"money" + 0.042*"gud" + 0.036*"to" + '
  '0.025*"transfer" + 0.023*"account" + 0.017*"correct" + 0.014*"how" + '
  '0.013*"can"'),
 (7,
  '0.203*"app" + 0.169*"nice" + 0.124*"excellent" + 0.106*"great" + '
  '0.059*"awesome" + 0.042*"it" + 0.040*"love" + 0.030*"fantastic" + '
  '0.028*"perfect" + 0.027*"wonderful"'),
 (8,
  '0.083*"satisfactory" + 0.062*"you" + 0.049*"well" + 0.040*"job" + '
  '0.038*"thanks" + 0.034*"thank" + 0.021*"opay" + 0.019*"really" + '
  '0.018*"excited" + 0.016*"doing"'),
 (9,
  '0.153*"it" + 0.096*"like" + 0.064*"better" + 0.051*"work" + 0.037*"just" + '
  '0.018*"star" + 0.016*"more" + 0.015*"me" + 0.011*"enough" + 0.010*"loan"')]
```

Figure 4: Visualization of LDA topics

Discussion

The sentiment analysis of Opay Wallet user feedback yielded the following distribution of sentiments across the 160,890 user reviews collected from various platforms: 132,244 reviews were classified as positive, 21,782 as neutral, and 8,864 as negative. The majority of the feedback was positive, accounting for approximately 82.2% of the total reviews, while neutral reviews made up 13.5%, and negative reviews constituted 5.5%. This distribution indicates a generally favorable perception of Opay Wallet among users, with the platform receiving overwhelming positive sentiment from the majority of reviewers. The bar chart in Figure 3 presents a visualized result showing the responses labeled as Positive, Negative, and Neutral.

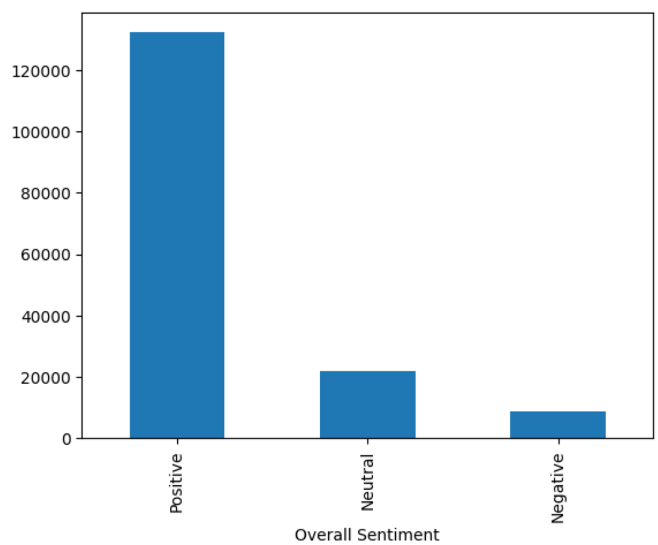

Figure 5: Bar Chart showing the categories of the responses

Further examination of the sentiment within the positive reviews revealed that users frequently praised the app's ease of use, convenience, and seamless transaction experience. Many highlighted the speed of transactions, especially in comparison to traditional banking methods, as a key factor in their satisfaction. Positive sentiments were also commonly associated with Opay Wallet's reward programs and incentives for frequent users, as well as its integration with other payment services.

In contrast, negative sentiments were often related to specific issues, including transaction failures, slow processing times, and difficulties with customer service. Users also voiced concerns over security features, mentioning experiences with fraudulent transactions or difficulties in resolving security issues. Despite these concerns, the overall proportion of negative feedback was relatively low compared to positive reviews, suggesting that while there are pain points, they affect a minority of users.

The neutral sentiment category was populated by reviews that were more focused on providing feedback about the app's functionality without expressing strong positive or negative emotions. Some users offered constructive feedback on potential improvements without indicating dissatisfaction, such as requesting additional features or modifications to the user interface.

The provided LDA output in Figure 4 consists of ten topics identified from user reviews of the Opay Wallet. Each topic is represented by a set of words with associated weights, indicating the relevance of the words to the topic. The interpretation of the topics based on the keywords and their relative importance is:

Topic 0: Exceptional Quality

This topic is characterized by keywords like "best," "exceptional," "wow," "application," and "banking." It reflects users expressing strong positive feedback, highlighting the app as one of the best they have experienced. Words like "exceptional" and "wow" suggest enthusiastic praise, possibly for the overall functionality and quality of the platform.

Topic 1: General Satisfaction

Keywords such as "ok," "okay," "fine," "splendid," and "satisfied" indicate moderate or positive feedback. Users in this group appear to acknowledge the app's adequacy and express contentment, albeit without strong emotional intensity. This topic represents users who find the service acceptable but are not overwhelmingly impressed.

Topic 2: Fair Experience

Words like "fair," "satisfying," "real," and "now" suggest that this topic focuses on users who perceive the app as adequate or average. The inclusion of "wa" and "sha" may indicate informal language usage, suggesting mixed or regionally influenced sentiment.

Topic 3: Negative Feedback – Technical Issues

Keywords such as "bad," "not," "network," "slow," and "update" highlight user dissatisfaction with technical aspects of the app, such as poor network performance, slow functionality, or a need for updates. This topic points to a subset of users who encountered technical frustrations with the platform.

Topic 4: Service Quality Issues

This topic is dominated by "service," "poor," "no," and "never," suggesting dissatisfaction with customer service or service delivery. Negative words like "poor" and "never" emphasize frustration, potentially related to unresponsive customer support or unmet expectations.

Topic 5: Strong Positivity

Keywords like "good," "very," "cool," "reliable," and "fast" indicate highly positive feedback. Users in this category express satisfaction with the app’s reliability, speed, and overall quality. This topic represents a significant portion of satisfied users who find the platform effective and trustworthy.

Topic 6: Financial Transactions and Concerns

Words such as "money," "transfer," "account," and "correct" suggest feedback related to financial transactions. Users might be discussing successes or challenges with transferring funds or managing their accounts, highlighting the importance of smooth financial operations.

Topic 7: Praise for the App

This topic features terms like "app," "nice," "excellent," "great," and "awesome," reflecting enthusiastic approval of the platform. Users frequently use highly positive descriptors, emphasizing satisfaction with the app's design, usability, or performance.

Topic 8: Gratitude and Satisfaction

Keywords like "satisfactory," "thank," "thanks," "job," and "excited" suggest users expressing gratitude and appreciation for the app's performance. This feedback indicates users acknowledge the platform's contributions to improving their financial transactions.

Topic 9: Room for Improvement

Words such as "better," "work," "like," "just," and "more" indicate users who appreciate the app but see opportunities for improvement. This topic likely includes constructive criticism and requests for enhanced features or services.

General Insights

i. Predominance of Positive Feedback: Topics 0, 5, 7, and 8 reveal significant positive sentiment, with users praising the app's quality, performance, and reliability.
ii. Constructive Neutral Feedback: Topics 1, 2, and 9 suggest a segment of users who are generally satisfied but highlight potential improvements.
iii. Key Pain Points: Topics 3 and 4 emphasize areas of dissatisfaction, such as technical glitches and customer service challenges.

Table 3 provides a detailed comparison of the findings from this study with the results obtained by other researchers, highlighting the methodology and result obtained.

Table 3: Comparison of result with other research

Author	Methodology	Result
Rusydiana and As-Salafiyah, 2022	Conducted sentiment analysis on Twitter data related to Shariah-compliant fintech.	neutral sentiment 80.8%, positive sentiment 16.2%, negative sentiment 3.0%
Zahra and Alamsyah, 2022	DANA, an Indonesian digital wallet application, was analyzed for service quality using Naïve Bayes classification and sentiment analysis.	The study found that the most significant issue in the digital wallet is customer compensation, with over 69% positive sentiments across all dimensions.
Renaldi, 2023	Twitter's RapidMiner tool was used in a study to analyze 3878 tweets	The Study revealed that users in Indonesia are more likely to give negative comments about electronic wallets. The accuracy rate for classifying positive and negative sentiments reached 88.56%.
This Work	Opay Wallet, a popular mobile payment platform, was analyzed using TextBlob and LDA to analyze user reviews from the Google Play Store	The study revealed a favorable perception of the platform, with 82.2% of reviews being positive, 13.5% were neutral, and 5.5% were negative

CONCLUSION

The combined findings from the LDA topic modeling and sentiment analysis of Opay Wallet user feedback provide a comprehensive understanding of user perceptions. The sentiment analysis results indicate that 82.2% of users have a positive outlook on the platform, appreciating its ease of use, speed, and reliability. The LDA analysis complements this by identifying recurring themes such as exceptional service quality, seamless transactions, and user satisfaction, with positive keywords dominating the topics. However, the presence of 13.5% neutral and 5.5% negative sentiments highlights areas for potential improvement. Negative feedback centers on technical issues, such as slow transactions and network problems, and dissatisfaction with customer service, which aligns with themes extracted from the LDA topics like "Technical Issues" and "Service Quality Problems". The insights also reveal that while many users are highly satisfied, some remain neutral, indicating unmet needs or suggestions for enhancements. Topics such as "Room for Improvement" emphasize the importance of continually evolving the platform to meet user expectations. Neutral feedback often includes constructive suggestions, such as requests for additional features, a smoother user interface, and broader service integration, which, if addressed, can turn indifferent users into loyal customers. To maintain its strong reputation and address areas of concern, Opay Wallet should prioritize improving its technical infrastructure to minimize transaction failures and network issues. Implementing more robust systems to ensure reliability during peak usage times will enhance user trust. Additionally, upgrading security features and fraud detection mechanisms is crucial to alleviate concerns related to financial safety and data protection. These measures will address the critical pain points raised by dissatisfied users. Furthermore, Opay Wallet should enhance its customer support services by providing faster, more efficient responses to user complaints. Establishing a 24/7 support system with clear resolution timelines can significantly improve the user experience. To cater to users expressing neutral sentiments, Opay should consider introducing innovative features, such as expanded payment options, customizable user interfaces, and localized services tailored to specific customer needs. Finally, leveraging user feedback for continuous improvement and launching targeted marketing campaigns that highlight the app's strengths can reinforce positive sentiment and foster greater customer loyalty.

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