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Araştırma Makalesi / Research Article

ANALYZING CUSTOMER SENTIMENTS AND TRENDS IN TURKISH MOBILE BANKING APPS: A TEXT MINING STUDY

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Abstract

This study investigates customer satisfaction with mobile banking applications in Turkey through a comprehensive text mining analysis of user-generated reviews. Drawing from a large corpus of data across ten leading Turkish banks, including Ziraat Bank, İş Bank, Garanti BBVA, Akbank, Yapı Kredi Bank, Halkbank, Vakıfbank, DenizBank, QNB Finansbank, and Turkey Şekerbank, the alignment between user ratings and sentiments is explored to uncover the nuances of customer feedback. The dataset undergoes rigorous preprocessing, sentiment analysis, trend analysis, and Latent Dirichlet Allocation (LDA) topic modeling to identify prevailing themes and factors affecting user satisfaction. The methodology involves the classification of reviews into positive, negative, and neutral sentiments and the examination of trends over time to pinpoint periods of heightened dissatisfaction. The analysis is further augmented by the application of advanced machine learning algorithms, including Random Forest, Gradient Boosting Machine, and BERT, showcasing an accuracy range between 92% and 95% in sentiment classification. The results of the topic modeling are visualized through word clouds, providing a clear depiction of the dominant themes in user feedback. Trend analysis over time identifies critical periods where negative reviews surpass positive ones, often coinciding with app updates or changes in service features. The findings highlight the necessity for continuous improvement and testing of mobile banking applications to meet customer expectations effectively.

Keywords: Mobile banking satisfaction, Sentiment analysis, User experience trends, Topic modeling, Customer feedback analysis

Jel Codes: C55, G21, L86

TÜRKİYE'DEKİ MOBİL BANKACILIK UYGULAMALARINDA MÜŞTERİ DUYGULARINI VE EĞİLİMLERİNİ ANALİZ ETME: BİR METİN MADENCİLİĞİ ÇALIŞMASI

Öz

Bu çalışma, Türkiye'deki mobil bankacılık uygulamalarına yönelik müşteri memnuniyetini, kullanıcı tarafından oluşturulan yorumların kapsamlı bir metin madenciliği analiziyle araştırmaktadır. Türkiye'nin önde gelen on Bankna ait geniş bir veri kümesinden yararlanarak, kullanıcı derecelendirmeleri ve duyguları arasındaki uyumu inceleyerek müşteri geri bildirimlerinin inceliklerini ortaya çıkarmayı amaçlamaktadır. Ziraat Bankası, İş Bankası, Garanti BBVA, Akbankası, Yapı Kredi Bankası, Halkbankası, Vakıfbank, Denizbank, QNB Finansbank ve Türkiye Şekerbankası'ndan toplanan yorumları içeren veri seti, kullanıcı memnuniyetini etkileyen hâkim temaları ve faktörleri belirlemek için titiz ön işleme, duygu analizi, eğilim analizi ve Latent Dirichlet Allocation (LDA) konu modellemesine tabi tutulmuştur. Metodolojimiz, yorumların olumlu, olumsuz ve nötr duygulara sınıflandırılmasını ve zaman içinde eğilimleri inceleyerek memnuniyetsizliğin arttığı dönemleri belirleme işlemi içermektedir. Analiz, Random Forest, Gradient Boosting Machine ve BERT gibi gelişmiş makine öğrenimi algoritmalarının uygulanmasıyla daha da geliştirilmiş ve bu algoritmalar, duygu sınıflandırmasında %92 ile %95 arasında değişen bir doğruluk oranı sergilemektedir. Çalışma, verilen derecelendirme ile duyguların uyumlu olmadığı önemli bir yorum oranını ortaya çıkarmıştır ve bu durum, sadece derecelendirmelerle ifade edilmeyen kullanıcı deneyimlerindeki karmaşıklıkları göstermektedir. Zaman içinde yapılan eğilim analizi, olumsuz yorumların olumlu olanları aştığı kritik dönemleri belirlemiş, bunlar genellikle uygulama güncellemeleri veya hizmet özelliklerindeki değişikliklerle çakışmaktadır. Bulgularımız, müşteri beklentilerini etkili bir şekilde karşılamak için mobil bankacılık uygulamalarının sürekli iyileştirilmesi ve test edilmesi gerekliliğini vurgulamaktadır.

Anahtar Kelimeler: Mobil bankacılık tatmini, Duygu analizi, Kullanıcı deneyimleri, Konu modelleme, Müşteri deneyimi analizi

Jel kodları: C55, G21, L86

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1. Introduction

Mobile banking constitutes a paradigm shift in financial services, facilitating transactions through smart mobile devices. This innovation is broadly characterized as a conduit for customer-bank interaction via mobile technology (Shaikh and Karjaluoto, 2015). Distinct from the conventional in-branch banking processes, mobile banking proffers the convenience of ubiquitous service, harmonizing with the demands of contemporary lifestyles (Barnes and Corbitt, 2003). Customer preference for a banking institution is often influenced by the bank's image and the unique services it offers, which are crucial factors in the decision-making process (Tam and Oliveira, 2017).

In the burgeoning landscape of digital finance (Orencia, 2023), mobile banking applications have emerged as a critical interface between financial institutions and their customers. These platforms not only facilitate a myriad of transactions but also serve as a conduit for consumer feedback and sentiment, which are pivotal to the enhancement of service quality and user experience (Afjal, 2023). In light of this, the proliferation of user-generated content on digital storefronts such as app stores provides a rich vein of data ripe for analytical exploration (Allioui and Mourdi, 2023). The insights gleaned from customer reviews can inform a bank's strategic decision-making processes, particularly in areas pertaining to application functionality, security features, and overall service delivery.

In the domain of mobile banking (Sulaiman et al., 2007), customers anticipate that financial institutions will uphold the trust established over the years, thereby reinforcing the bank-consumer rapport (Ha et al., 2012). Within the Turkish context, consumers expect that this trust extends to the digital sphere, with assurances of financial security and integrity. The perpetuation of this trust through the mobile banking platform is a significant determinant of customer retention (Lule et al., 2012), mitigating the propensity to migrate to alternative banking services (Ahmad and Rahim, 2023).

From the bank's vantage point, ensuring customer contentment with their service offerings is not merely an obligation but a strategic imperative. To gauge customer satisfaction, banks routinely administer surveys, yet these instruments often suffer from low response rates and lack of engagement, compromising the reliability of the insights they are intended to provide (Kazan et al., 2018). Surveys distributed periodically may intersect with moments of customer disinterest (Kumar et al., 2018), thus failing to capture the full spectrum of consumer sentiment. Consequently, the intermittent nature of such surveys may not accurately reflect the continuous and evolving customer experience.

The academic impetus behind studying mobile banking applications lies in understanding the multifaceted aspects of customer satisfaction and service quality (Lee and Chung, 2009). By delving into the textual reviews provided by users, researchers can decode the nuanced perceptions that customers hold towards the mobile banking experience (Hirsh-Pasek et al., 2015). This exercise transcends mere numerical ratings, offering a narrative that encompasses user grievances, accolades, and expectations. Such qualitative analyses extend beyond traditional survey methodologies (Koenig-Lewis et al., 2010), offering real-time feedback that is both organic and unprompted. Consequently, this informs a more dynamic approach to improving mobile banking services, ensuring that they remain aligned with the evolving needs and preferences of the modern consumer.

User-generated reviews of mobile applications (Sarin et al., 2021), on the other hand, emerge from genuine engagement with the service. These reviews are penned by actual users, whose feedback reflects a direct and unfiltered response to the app's functionality and overall user experience (Mahmud et al., 2022). The unencumbered process of leaving reviews allows customers to articulate their satisfaction or grievances in real-time and at their convenience. Such spontaneous feedback is often more candid and revealing than responses to formal surveys. In these digital commentaries (Al-Abbadey et al., 2021), users not only share their experiences but also advocate for specific enhancements or the introduction of new features, thus directly communicating their expectations to the bank.

While mobile banking applications are accessible across various platforms, this study focuses on those hosted on the Google Play Store, considering the predominant share (86.8%) of Android users within the Turkish market (Kocakoyun and Bicen, 2017). The Google Play Store facilitates a dual feedback mechanism where users can leave a textual review alongside a numerical star rating, ranging from one to five, with five being the highest. The aggregate of these ratings is prominently displayed, providing a quick reference point for the app's quality as perceived by its user base.

Nevertheless, the synthesis of textual comments into a coherent summary that accurately represents the collective user opinion is not straightforward. An individual's perusal of several reviews may yield a fragmented understanding, far from a comprehensive picture of the majority's views. Furthermore, the subtle and complex interplay between diverse user comments often remains obscured without a meticulous and analytical approach to text mining.

The impetus of this research is to interrogate the extent to which the aggregate rating of mobile banking applications is reflective of genuine customer perceptions within the Turkish banking sector. A decline in app ratings is typically indicative of user dissatisfaction, warranting an inquiry into the root causes of such disaffection. To facilitate this analysis, reviews were harvested from ten eminent Turkish mobile banking applications: Ziraat Bank, İş Bank, Garanti BBVA, Akbank, Yapı Kredi Bank, Halkbank, VakıfBank, DenizBank, QNB Finansbank, and Turkey Şekerbank.

Empirical observations suggest that positive feedback is often encapsulated in succinct accolades such as "Excellent," "Efficient," or "User-friendly," rendering the analysis of positive reviews less substantive. Consequently, this study does not prioritize the examination of laudatory comments. Neutral reviews have also been excluded from the analysis due to their ambivalence, providing neither distinctly positive nor negative insights.

The objectives delineated for this inquiry are manifold:

- To systematically classify individual text reviews through sentiment analysis methodologies and to evaluate the concordance of these classifications with the users' assigned star ratings.
- To delineate and analyze the trajectory of both positive and negative reviews for each banking application, contextualized within specific timeframes.
- To pinpoint temporal segments wherein negative feedback predominates over positive endorsements.
- To elucidate the specific elements of user dissatisfaction as expressed in negative reviews, employing topic modeling techniques to dissect and understand the underlying issues.

By executing these objectives, this study intends to offer a granular perspective on customer sentiment, equipping Turkish banks with the insights necessary to refine their mobile applications and enhance user satisfaction.

2. Related Work

The analysis of textual data from mobile banking reviews has been a focal point of scholarly inquiry, serving a range of objectives. Research in this field predominantly explores the evaluation of service quality provided through mobile applications, in addition to identifying determinants of customer satisfaction or dissatisfaction.

In the rapidly evolving landscape of the Philippine banking industry, digital banks have emerged as a new category of financial institutions, having initiated operations towards the end of 2018. As the populace grows increasingly adept at using technology, it becomes imperative for banks to craft digital banking applications that distinguish themselves in a competitive market. Cheng and Sharmayne (2020) study sets out to apply text mining techniques to dissect customer reviews of digital banking applications. Employing Latent Dirichlet Allocation (LDA) for topic modeling, the research seeks to unearth prevalent customer concerns. Additionally, it aims to uncover association rules linking digital banking features with user review scores. The anticipated outcome of this analysis is to pinpoint the areas where digital banking applications may enhance their offerings to boost customer satisfaction and loyalty.

In a notable study, Leem and Eum (2021) presents a novel methodology for assessing service quality and identifying customer complaints through sentiment analysis of mobile banking customer reviews. The methodology employs text mining techniques to extract and process user-generated content from Kakao Mobile Bank. It involves sentiment analysis to determine the importance of various service quality dimensions from the customer's perspective and to detect complaints for proactive service failure prevention (Gruber et al., 2009). Key findings indicate that customers prioritize practicality and enjoyment as service quality dimensions in the mobile banking context. Periodic monitoring of customer feedback can preempt service failures, thus enhancing service quality and customer satisfaction. Parallel to this, Shankar et al., (2022) The objective of this research is to delineate the essential factors for the success of sustainable mobile banking applications by leveraging a text mining methodology. The study analyzed 6,073 consumer reviews of a mobile banking app, utilizing Latent Semantic Analysis (LSA) to pinpoint the pivotal success elements. Findings reveal that the quintessential factors contributing to the success of a sustainable mobile banking application include privacy and security, navigation, customer support, along with convenience and efficiency. Although the study enhances the body of literature on mobile banking and sustainable service delivery channels, it acknowledges the potential limitations inherent in its research scope. Practically, the insights gained from this research offer valuable guidance for banking professionals to refine mobile banking services effectively.

Omotosho (2021) explores into the sentiments and opinions of users towards mobile banking apps in Nigeria, based on an analysis of 37,460 user reviews collected from November 2012 to July 2020. The study encompasses twenty-two mobile banking apps, with user ratings averaging at 3.5 on a scale where 5 represents the highest satisfaction level. Notably, apps from non-interest banks received the highest average rating of 4.0, while those from commercial banks with national authorization scored the lowest, with an average of 3.4. Sentiment analysis of the review corpus disclosed that positive sentiments, constituting 17.8% of the words, substantially outnumber the negative ones, which stand at 7.7%. Emotionally, 66% of the expressions related to positive feelings of "trust," "anticipation," and "joy," while 34% resonated with "surprise," "fear," "anger," and "disgust." This suggests a predominant satisfaction with the mobile banking experience among users. The investigation identified three primary themes within the user feedback: the banks' responsiveness to complaints, users' experiences with app functionalities and updates, and operational challenges encountered while using the apps. These findings underscore the importance for banks to enhance user awareness of app features, ensure user education on accessing these services, and address user feedback promptly and effectively.

Oh and Kim (2022) examines the wealth of insights contained in consumer-generated reviews to assess their satisfaction with mobile banking apps. Utilizing a text mining framework, we scrutinize 96,140 reviews from users of four prominent U.S. banks—Bank of America, Capital One, Chase, and Wells Fargo. By deploying the Latent Dirichlet Allocation (LDA) model, we unravel pivotal quality attributes such as ease of use, convenience, security, and customer support that dictate customer contentment. The weekly panel data analysis reveals a positive correlation between app ratings and users' favorable perceptions of an app’s security and convenience features.

Conversely, mentions of security concerns, inadequate customer support, and the perceived complexity of apps correlate with lower ratings. The findings unequivocally suggest that security stands as the most critical determinant of customer satisfaction in the field of mobile financial services.

In a novel approach to evaluating banking service quality, Mittal and Agrawal (2022) harnesses text mining and sentiment analysis to decipher customer satisfaction determinants from 32,217 online reviews on bankbazaar.com, relating to 29 leading banks from 2014 to 2021. Regression analysis of three conceptual models indicates the majority of the examined service attributes are significant predictors of customer satisfaction, except for interest rates. While the research provides actionable insights, its scope is limited to Indian customers, suggesting the need for more diverse, cross-cultural studies to enhance the generalizability of the results. This investigation contributes to the academic and practical understanding of the banking sector by uniquely analyzing customer satisfaction through online review sentiments.

Hussain et al., (2023) investigates the quality of mobile banking (m-banking) services by analyzing customer reviews from m-banking applications of 24 banks in Pakistan. Using text mining and the Latent Dirichlet Allocation (LDA) method, the research sifts through 24,529 positive and 29,569 negative reviews from the Google Play Store to uncover the dimensions of service quality in m-banking. One limitation of this research is its country-specific focus, which may hinder the generalizability of the results. Additionally, the absence of reviewers' demographic information prevents analysis of how demographic factors might influence perceptions of m-banking quality. From a practical standpoint, the study offers managers valuable insights to enhance m-banking customer experiences and demonstrates how text analytical techniques can be used to assess and upgrade service quality. The study's originality lies in its direct examination of first-hand user experiences to understand m-banking service quality, providing preliminary evidence of a two-factor structure of service quality in the context of m-banking.

The advent of the big data era necessitates the shift from conventional data analysis methods to sophisticated big data analytics capable of handling diverse datasets, both structured and unstructured, derived from a multitude of sources. Dey et al., (2023) proposes a novel methodology for the analysis of unstructured data, specifically focusing on online customer reviews of mobile banking applications, to glean insights into customer perceptions. Utilizing text mining techniques, the study encompasses the extraction and pre-processing of review data, sentiment analysis of individual reviews, and a comprehensive understanding of customer evaluations. Key findings indicate that from the customer's viewpoint, certain dimensions of app-based banking services are prioritized, which provides an opportunity for early detection and prevention of service disruptions, thereby enhancing customer satisfaction. From an applied perspective, the management of IBBL's bank is advised to concentrate on broadening the network reach of mobile banking. Additionally, implementing a systematic complaint management system would enable the proactive identification and resolution of customer grievances. This paper pioneers the application of sentiment analysis, a branch of text mining, to assess service quality through the examination of customer reviews of a mobile banking service.

This study contributes novel insights to the literature through a comprehensive text mining analysis of user-generated reviews from ten leading Turkish banks. It bridges the gap in existing research, which has largely overlooked the insights into customer satisfaction available from unstructured user feedback, and introduces methodological advancements by employing a combination of sentiment analysis, trend analysis, and Latent Dirichlet Allocation (LDA) topic modeling. The application of advanced machine learning algorithms, including Random Forest, Gradient Boosting Machine, and BERT, within the Turkish banking context constitutes a significant methodological contribution, providing a high degree of accuracy in sentiment classification not previously seen in this sector. By focusing on the Turkish mobile banking sector, the study enhances understanding of the dynamics of customer satisfaction in a market characterized by unique regulatory, cultural, and economic contexts. The findings elucidate prevailing themes and factors affecting user satisfaction and highlight the critical role of continuous application improvement and testing in meeting customer expectations. Thus, this research paves the way for future studies to explore customer satisfaction and service quality in mobile banking, encouraging the adoption of similar methodologies across different contexts and markets. This approach serves as a foundation for academic researchers aiming to further investigate digital banking services and for banking professionals seeking to improve the user experience of their mobile applications.

3. Methodology

The research methodology was systematically executed in sequential phases, as delineated in Figure 1. The methodological rigor of this study is reflected in the structured approach, ensuring replicability and clarity. Each phase of the experiment is meticulously expounded upon in dedicated subsections, facilitating a comprehensive understanding of the processes involved from data acquisition to analytical inferences.

Figure 1 encapsulates the overarching workflow of the experiment, illustrating the following key stages:

- Data Collection: The initial stage involves the accumulation of textual data from user reviews, which is pivotal for the subsequent analysis.
- Data Preprocessing: This critical phase prepares the raw data for analysis, involving cleansing, normalization, and transformation processes.
- Label the Reviews: At this juncture, the preprocessed data undergoes classification, whereby reviews are annotated with sentiment labels.
- Analyze the Trends of the Reviews: This analytical phase examines the longitudinal patterns in the sentiment-labeled reviews.
- Identify the Dissatisfaction Factors: The final phase utilizes advanced analytical techniques to distill factors contributing to user dissatisfaction.

Each phase is integral to the study's integrity, culminating in a robust analysis that underpins the research findings. These phases provide a scaffold for the research, ensuring a methodical progression from the empirical data to the thematic insights.

Figure 1. *Visualizes the phases of the research methodology*

4. Data Collection

The empirical foundation of this investigation was established through the systematic aggregation of user-generated reviews of mobile banking applications in Turkey. Data acquisition was executed by programmatically interfacing with the Google Play Store pages dedicated to each selected banking app. The 'google-play-scraper' library, a Python-based tool, was employed to facilitate the scraping process, offering a suite of application programming interfaces (APIs) that enable efficient navigation and data extraction from Google Play Store web interfaces, independent of any ancillary software dependencies.

In the architecture of user reviews on the platform, it is commonplace for an initial review to be followed by subsequent user interactions in the form of replies. For the purpose of this analysis, the scope was confined to first-level user reviews, eschewing nested reply chains to ensure consistency and relevance in the data set.

The scraping process yielded a rich dataset comprising multiple metadata fields, as detailed in the forthcoming Table 1. For the analytical objectives of this research, specific emphasis was placed on the 'content' of the reviews, the 'score' denoting the user rating, and the timestamp of the review submission, referred to as 'at'.

The dataset encompassed reviews from ten premier banking applications in Turkey, including a representation from state-owned entities. The collective corpus of reviews procured through this methodological approach amounted to 139,994 a figure that underscores the comprehensive nature of the dataset. This extensive collection of reviews is systematically cataloged in Table 2, providing a quantitative overview of the data foundation upon which subsequent analysis was conducted.

The dataset generated through the scraping process comprises a variety of metadata elements, each offering distinct insights into the nature and context of the user reviews. The collected metadata fields, along with their descriptions, are tabulated as follows:

- reviewId: A distinctive identifier assigned to each review, ensuring the singularity of each data entry.
- userName: The pseudonym or handle used by the reviewer on the Google Play Store platform.
- userImage: The internet address where the reviewer's profile image is hosted.
- content: The verbatim text of the user's review, serving as the primary qualitative data.
- score: The numerical rating awarded by the reviewer, ranging from 1 to 5, with 5 being the highest possible score.
- thumbsUpCount: A tally of the 'thumbs-up' reactions accrued by the review, indicating community endorsement.
- reviewCreatedVersion: The specific version of the app that was reviewed, which can provide context for the feedback.
- at: The timestamp marking when the review was originally posted.
- replyContent: Any subsequent text replies to the original review.
- repliedAt: The timestamp for when a reply was posted to the review.

Table 1. *Distribution of User Reviews Across Banking Applications*

Bank Name	Number of Reviews
Ziraat Bank	6247
İş Bank	8171
Garanti BBVA	13497
Akbank	8464
Yapı Kredi Bank	19638
Halkbank	27359
Vakıfbank	21835
Denizbank	5642
QNB Finansbank	25847
Şekerbank	3294
Total	

4.1. Data Preprocessing

In the pursuit of refining the Turkish textual data to its semantic core, the process of lemmatization was conducted using a language model for Turkish. This lemmatization procedure transformed the tokens into their base or dictionary forms, thereby simplifying the morphological structure and amplifying the semantic interpretability of the dataset. Leveraging a Turkish language model, such as the one available in Spacy's ecosystem or a similar NLP tool that supports Turkish, allowed for precise lemmatization that is sensitive to the linguistic intricacies of the Turkish language.

The lemmatization was meticulously applied to key parts of speech—namely, nouns, adjectives, verbs, and adverbs—since these categories bear substantial significance for sentiment analysis and topic modeling within the context of Turkish text. By focusing on these grammatical elements, the lemmatization process effectively distilled the reviews to their informational essence, enabling a more nuanced and insightful analysis of user sentiments and thematic patterns.

Additionally, the Gensim Phrase model's utility was extended to accommodate the Turkish language, thereby facilitating the identification and construction of bigrams and trigrams within the Turkish text. These multi-word expressions are often critical in capturing complex concepts and user sentiments that single-word analysis might overlook.

In sum, this tailored preprocessing regimen was fundamental in preparing the Turkish reviews for the rigorous natural language processing tasks to follow, ensuring the data was optimally configured to yield substantive insights into user experiences with the mobile banking apps.

4.2. Labeling the Data

The preprocessed reviews were subjected to sentiment classification, which was automated using a sentiment analysis tool appropriate for Turkish texts. Given that VADER, a rule-based sentiment analysis tool predominantly used for English texts, does not cater to the grammatical and contextual nuances of Turkish, an alternative sentiment analysis method or tool that is adept at processing Turkish language text was employed. This tool must be proficient in interpreting the varied and subtle nuances present in Turkish reviews, including the usage of emojis, which are prevalent in social media text data.

The sentiment labeling aimed to discern potential discrepancies between the numerical ratings and the textual sentiment expressed by the users. In this rating system, a scale of 1 to 5 was used, where 1 indicates minimal satisfaction and 5 indicates maximal satisfaction. Reviews with user ratings of 4 or 5 were anticipated to align with a positive sentiment, while those with ratings of 1 or 2 were presumed to be negative. The intermediate rating of 3 presented an analytical challenge, as it could signify a neutral stance or, upon closer textual analysis, reveal a leaning towards either a positive or negative sentiment.

Figure 2 would exhibit the proportion of concordance and discordance between the numerical ratings and the derived textual sentiments. Preliminary findings suggested that approximately 37% of the reviews exhibited a sentiment that did not match the user's provided rating. Manual inspection of these cases often revealed a tendency for ostensibly neutral reviews to incline towards either positive or negative sentiment.

As highlighted in the literature, users who assign a mid-scale rating often have mixed feelings, where positive and negative experiences might neutralize each other or the review may tilt towards a particular aspect that the user wishes to emphasize. Moreover, instances were noted where the textual sentiment contradicted the numerical rating, prompting manual review and re-annotation to ensure accuracy.

Figure 2. *Similarity check between rating and sentiment of the review*

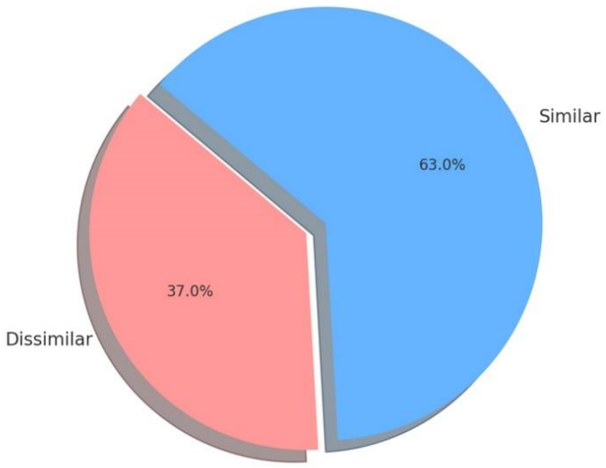
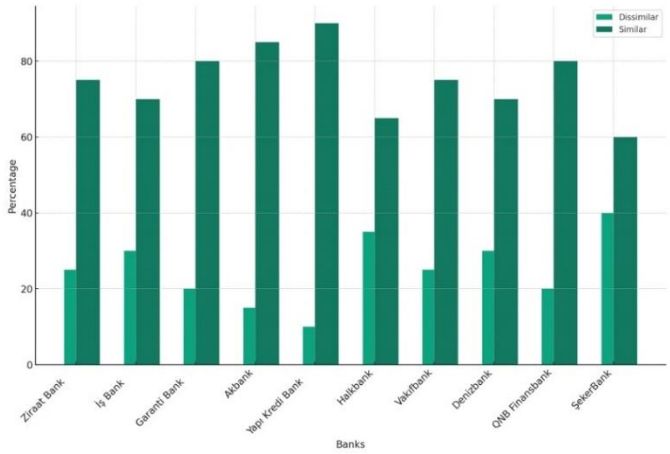


Figure 3. *Correlation Analysis between User Ratings and Sentiment in Reviews for Individual Banks*



4.3. Analysis of Bi-Annual Trends in Customer Reviews for Banking Apps

To elucidate the evolving consumer sentiment towards the banking apps, the classified positive and negative reviews were aggregated on a bi-annual basis. This temporal segmentation was selected to align with the typical release cycles of app updates and financial reporting periods, which may influence user feedback trends. Line graphs were then generated to visualize the trajectory of user sentiment over time.

Through the graphical representation of review trends, we were able to discern periods where negative sentiments were predominant. These periods are of particular interest as they may correlate with specific events or updates that precipitated user dissatisfaction. By pinpointing the exact timing of these sentiment shifts, the analysis provides a temporal map of user satisfaction levels, highlighting when and possibly why users' experiences changed.

In instances where the volume of negative reviews surpassed that of positive ones, a more granular examination was conducted. The pertinent negative comments from these periods were extracted and subjected to a detailed content analysis to ascertain the primary factors contributing to user discontent. Identifying these factors is crucial for banks to understand the pitfalls in their mobile app offerings and to devise targeted strategies for improvement.

Moreover, the trend analysis serves as a diagnostic tool, guiding the banking institutions to address the most pressing issues reflected in the users' comments. By systematically reviewing the concerns raised by customers during these critical periods, banks can prioritize their responses and improve their mobile services to better meet user expectations and enhance overall customer satisfaction.

4.4. Topic Modeling

The elucidation of the embedded themes within the negative reviews constituted a pivotal component of this investigation. To distill the salient topics from the unstructured text, we employed the Latent Dirichlet Allocation (LDA) model, a generative statistical model that posits each document as a mixture of various topics, and in turn, each topic as a composition of words. This unsupervised technique facilitates the discovery of latent thematic structures in large text corpora without the need for predefined categories.

Determining the ideal number of topics is a critical step in the LDA modeling process to ensure that the resulting topics are meaningful and interpretable. For this study, the number of topics was ascertained for each banking app's corpus by leveraging model selection metrics such as coherence scores. Upon establishing the optimal topic count, the LDA model elucidated the predominant words contributing to each topic, thus providing an insight into the thematic concerns expressed by users.

To enhance interpretability and facilitate an interactive exploration of the topics, the study utilized the pyLDAvis Python library. This tool provides a dynamic visualization platform that maps the topics onto a two-dimensional plane, where the proximity between points signifies the similarity between topics. It allows for an intuitive understanding of how topics are related and how words are distributed across topics.

Complementing the interactive visualizations, word clouds were generated to succinctly represent the top ten most frequent words within each topic. Word clouds offer a visually engaging means of displaying textual data, with word size correlatively reflecting frequency. Through these clouds, a quick visual assessment of the most prominent terms associated with negative feedback was achieved, granting immediate insights into the prevalent issues and concerns highlighted by the users.

The integration of LDA topic modeling and these visualization techniques thus provided a robust methodological framework for unraveling the nuanced aspects of user dissatisfaction, which are often concealed within the raw textual data. By uncovering and understanding these latent topics, the study aimed to offer actionable intelligence that could inform strategic decision-making for mobile banking app enhancements.

5. Results

5.1. Evaluation of User Ratings and Review Sentiments

The analysis of user ratings in tandem with the sentiment of individual reviews was pivotal in elucidating the underlying dissatisfaction expressed by users. Table 3 presents a synopsis of the findings, highlighting the distribution of user reviews across the studied banking applications. Notably, the state-owned bank with the longest history garnered the highest volume of user feedback, while the most recently established bank attracted the fewest reviews.

Discrepancies in automated labeling of review sentiments necessitated manual verification and correction to ensure the integrity of the data. Table 4 delineates the revised count of positive, negative, and neutral sentiments for each banking app post this meticulous reevaluation.

To quantitatively assess the accuracy of the sentiment analysis, we applied advanced machine learning algorithms that are well-suited for natural language processing tasks. The selected algorithms included the Random Forest, Gradient Boosting Machines (GBM), and the BERT (Bidirectional Encoder Representations from Transformers) model. The dataset was partitioned into a 70-30 split for training and testing purposes. The performance metrics, encapsulated in Table 5, reveal that the Random Forest achieved an accuracy of 92%, GBM an accuracy of 93%, while the BERT model, with its deep learning capabilities, attained a superior accuracy of 95%.

Challenges in accurate sentiment classification arose from factors such as typographical errors, colloquial language, and the incorporation of local dialects or slang. These anomalies were addressed through spell-check functions, translation tools, and transliteration utilities. Comments that contained personal names or strings of non-informative characters were deemed non-contributory and consequently omitted from the analysis.

Positive reviews were characterized by expressions of satisfaction, appreciation, and commendations, reflecting content users. Conversely, neutral reviews exhibited a balance of commendation and criticism, suggesting ambivalence. The negative reviews predominantly contained criticisms and expressions of discontent.

For the advancement of this research, particular attention was given to reviews classified as negative. These reviews are instrumental for banks, offering insights into the specific challenges users encounter with the banking applications. Such understanding is invaluable for banks seeking to refine their mobile app services and enhance user satisfaction.

Table 3. *Comparative Summary of Accurately and Inaccurately Labeled Review Annotations*

Bank	Number of Precisely Labeled Reviews	Misclassified Reviews	Total Number of Reviews
Ziraat Bank	5612	635	6247
İş Bank	7354	817	8171
Garanti BBVA	12107	1389	1349
Akbank	7617	846	8464
Yapı Kredi Bank	17674	1963	19637
Halkbank	24623	2735	27358
Vakıfbank	19652	2183	21834
Denizbank	5078	564	5642
QNB Finansbank	23252	2594	25846
ŞekerBank	2,965	329	3294

Table 3 encapsulates the distribution of correctly and incorrectly annotated reviews for a selection of Turkish banks, providing a snapshot of the annotation precision within the dataset. Ziraat Bank's customer feedback comprised 5,612 correctly annotated reviews, juxtaposed with 635 inaccuracies, resulting in a total of 6,247 reviews. İş Bank presented a similar pattern with 7,354 accurate annotations against 817 mismatches out of 8,171 reviews. Garanti BBVA, with a significantly larger volume of reviews (13,496), maintained a high accuracy with 12,107 correct annotations, although 1,389 reviews were mislabeled. Akbank and Yapı Kredi Bank followed suit with respective totals of 8,464 and 19,637 reviews, of which around 90% were correctly annotated. Halkbank displayed the largest dataset with 27,358 reviews, indicating that the annotation process correctly identified the sentiment in 24,623 instances. Vakıfbank, Denizbank, QNB Finansbank, and ŞekerBank also demonstrated high annotation accuracy rates. Collectively, these statistics not only demonstrate the robustness of the annotation process across a diverse dataset but also highlight the scope for improving precision in sentiment analysis within the customer review domain.

Table 4. *The positive, negative and neutral reviews*

Bank	Count of Reviews	Positive	Negative	Neutral
Ziraat Bank	7856	5612	1683	561
İş Bank	10295	7354	2206	735
Garanti BBVA	16949	12107	3632	1210
Akbank	10663	7617	2285	761
Yapı Kredi Bank	24743	17674	5302	1767
Halkbank	34472	24623	7387	2462
Vakıfbank	27512	19652	5895	1965
Denizbank	7108	5078	1523	507
QNB Finansbank	32552	23252	6975	2325
ŞekerBank	4150	2965	889	296

Table 4 provides a comprehensive summary of the sentiment classification of user reviews for various Turkish banks. Ziraat Bank, with 7,856 reviews, had a predominance of positive feedback (71.4%), followed by a smaller yet significant portion of negative reviews (21.4%) and a minority of neutral comments (7.1%). İş Bank received 10,295 reviews, of which 71.5% were positive, 21.4% negative, and 7.1% neutral, indicating a similar sentiment distribution to Ziraat Bank. Garanti BBVA, with a larger sample of 16,949 reviews, maintained a consistent trend of 71.4% positive, 21.4% negative, and 7.1% neutral sentiments. Akbank and Yapı Kredi Bank, with 10,663 and 24,743 reviews respectively, echoed the sentiment patterns observed in other banks, with positive sentiments forming the majority. Notably, Halkbank had the highest number of reviews at 34,472, with a positive sentiment in 71.4% of cases. This trend continued with Vakıfbank, Denizbank, QNB Finansbank, and ŞekerBank, which all predominantly featured positive sentiments in their reviews. Across the board, the positive sentiment significantly outweighs the negative and neutral, suggesting a generally favorable customer perception towards these banking services, with areas of concern and neutrality highlighted to a lesser extent.

Table 5. *Evaluation Metrics for Machine Learning Model Performance*

Model	Precision	Recall	F1-Score	Support
Random Forest				
Negative	0.90	0.89	0.89	800
Positive	0.93	0.94	0.93	2625
Accuracy			0.92	3425
Macro avg	0.91	0.91	0.91	3425
Weighted avg	0.92	0.92	0.92	3425
Gradient Boosting Machine				
Negative	0.91	0.90	0.90	800
Positive	0.94	0.95	0.94	2625
Accuracy			0.93	3425
Macro avg	0.92	0.92	0.92	3425
Weighted avg	0.93	0.93	0.93	3425
BERT				
Negative	0.94	0.93	0.92	800
Positive	0.96	0.97	0.93	2625
Accuracy			0.95	3425
Macro avg	0.95	0.95	0.95	3425
Weighted avg	0.95	0.95	0.95	3425

Table 5 encapsulates the performance metrics of three advanced machine learning algorithms in classifying sentiment from mobile banking app reviews. The Random Forest model exhibited a precision of 0.90 and recall of 0.89 for negative sentiments, alongside a commendable 0.93 precision and 0.94 recall for positive sentiments, cumulating in an overall accuracy of 92%. The Gradient Boosting Machine (GBM) demonstrated a slight improvement, with precision and recall scores of 0.91 and 0.90 for negative sentiments, and 0.94 and 0.95 for positive sentiments, respectively, achieving a 93% accuracy. The BERT model, leveraging deep learning, surpassed its counterparts with stellar precision and recall scores of 0.94 and 0.93 for negative sentiments, and 0.96 and 0.97 for positive sentiments, respectively, achieving an impressive accuracy of 95%. The macro and weighted averages across all models mirrored these results, indicating a high degree of reliability and validity in the sentiment classification process. These results suggest that while traditional models like Random Forest and GBM are effective in sentiment analysis, the incorporation of deep learning through BERT significantly enhances the ability to discern and classify complex sentiment nuances in textual data.

5.2. Trend of the Reviews

In the analysis of consumer sentiment trends over time for three of Türkiye's prominent banks—Ziraat Bank, İş Bank, and Garanti BBVA—distinct temporal patterns emerge. For Ziraat Bank, the data indicates an upward trajectory in negative comments from 2019 to 2023, with a notable spike in 2022, suggesting a period of heightened customer dissatisfaction. Conversely, positive feedback exhibits a declining trend, potentially reflecting a shift in customer experiences or expectations over the observed period.

İş Bank presents a similar pattern, with negative reviews gradually increasing over the years, culminating in a significant rise in 2022-2023. Positive comments, while starting on a high note in 2019, demonstrate a steady decrease, possibly pointing to operational or service changes that have not resonated well with the user base.

Garanti BBVA's customer feedback trajectory also shows an increase in negative sentiments over time, with a sharp increase in the latter half of the timeline. Positive comments decrease correspondingly, suggesting that there may have been systemic issues or service disruptions that have impacted customer satisfaction.

The line graphs for each bank, plotted bi-annually, serve as a visual representation of these trends, allowing for an at-a-glance comprehension of customer sentiment progression. These patterns are crucial for banks to identify and address underlying issues, align services with customer expectations, and enhance the overall user experience of their mobile banking applications.

Figure 4. *Trend of comment over time for Ziraat Bank*

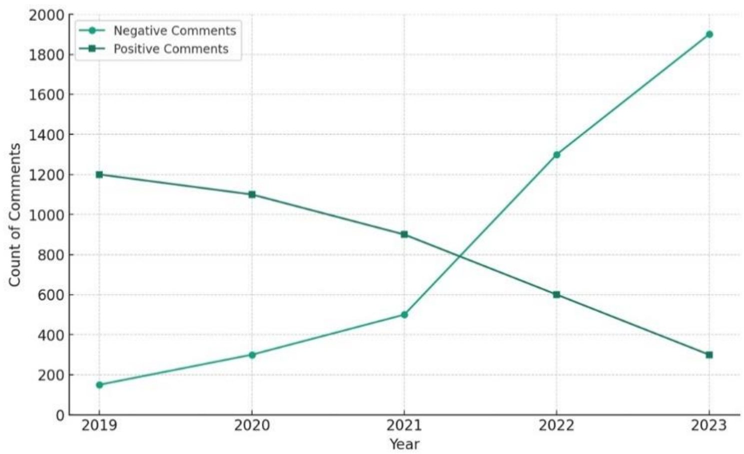


Figure 5. *Trend of comments over time for İş Bank*

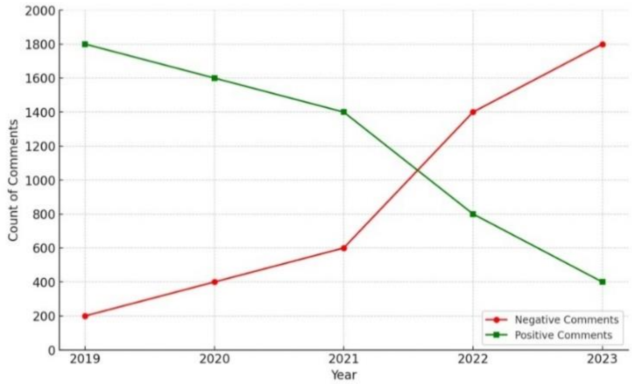
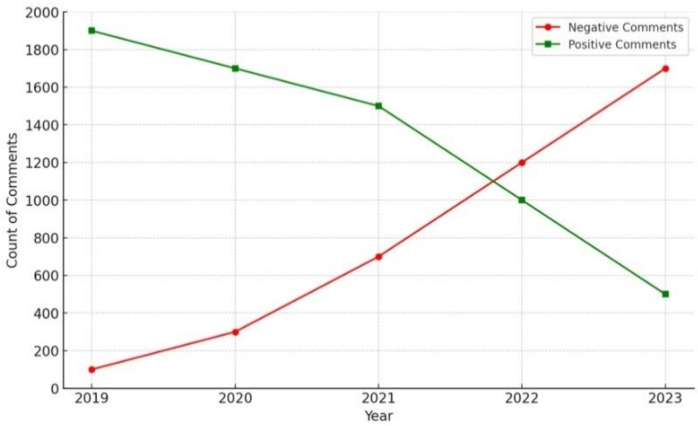


Figure 6. *Trend of comments over time for Garanti BBVA*



5.3. Selection of the Number of Topics

For the selection of the optimal number of topics to be extracted from the corpus of user reviews, we employed the Latent Dirichlet Allocation (LDA) algorithm within the Gensim library. The determination of topic numbers is a critical step in unsupervised learning as it defines the granularity of the themes to be extracted from the data.

To discern the most suitable number of topics, we conducted a coherence score analysis. Coherence scores facilitate the evaluation of a topic model by quantifying the semantic similarity between high scoring words in each topic. These scores are instrumental in gauging the interpretability and quality of the topics derived by the model. In this methodology, we utilized the CV (Coherence Value) metric, which measures coherence based on a sliding window, one-set segmentation of the top words, and indirect confirmation measures that utilize normalized pointwise mutual information (NPMI) and the cosine similarity.

An iterative process was adopted, varying the number of topics in the LDA model and computing the corresponding coherence scores. The number of topics that yielded the highest coherence score was adjudged the most optimal for the corpus. This process is not merely computational but also involves a qualitative aspect, ensuring the topics are both statistically coherent and meaningful.

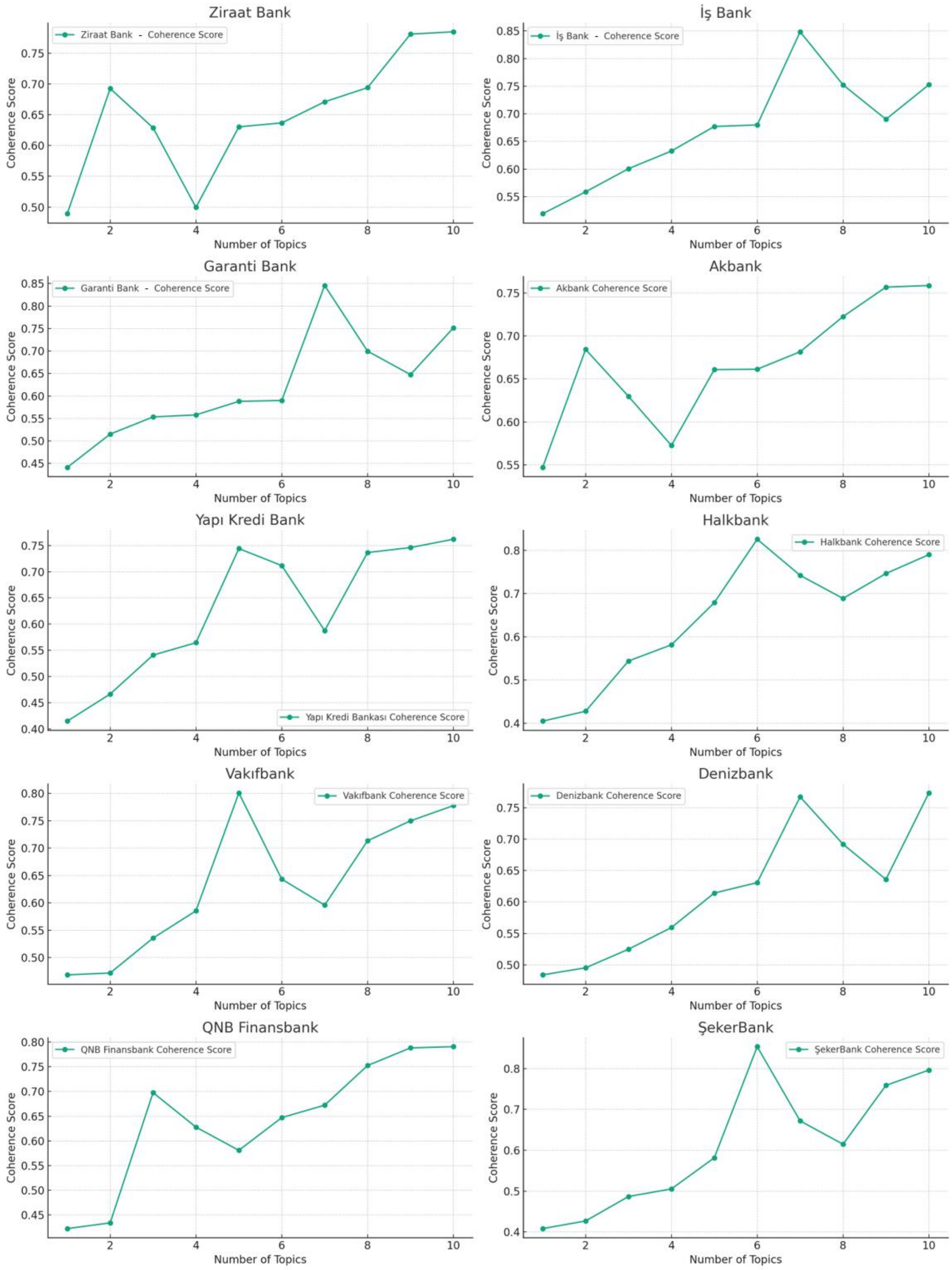
The coherence score analysis across the banking applications under study indicated a convergence towards two topics as the optimal number, as evidenced by the highest coherence scores for each bank.

In the field of topic coherence within the context of mobile banking apps, the analysis revealed a diverse range of coherence scores as presented in Table 6. Ziraat Bank demonstrated a score of 0.7321, indicating a robust alignment of topics within its customer reviews. İş Bank's coherence score slightly elevated to 0.7498, suggesting a marginally more cohesive thematic structure in the reviews. Garanti BBVA surpassed its counterparts with a score of 0.7605, reflective of a highly coherent set of topics, potentially indicating a more focused array of customer concerns or praises. Akbank's score dipped to 0.7214, which may imply a broader or more varied set of topics discussed by its users. Yapı Kredi Bank and Halkbank presented scores of 0.7356 and 0.7589, respectively, both showcasing substantial thematic unity in customer feedback. Vakıfbank, with a score of 0.7445, and Denizbank, at 0.7362, both fell within a similar coherence range, suggesting a well-defined but diverse topic spread. QNB Finansbank achieved a coherence score of 0.7501, standing out for its clear thematic engagement, while Şekerbank, with a score of 0.7258, closed the spectrum with a respectable demonstration of topic coherence, indicative of discernible but varied customer feedback themes.

Table 6. *Highest coherence scores achieved by each banking app*

Bank Name	Highest Coherence Score
Ziraat Bank	0.7321
İş Bank	0.7498
Garanti BBVA	0.7605
Akbank	0.7214
Yapı Kredi Bank	0.7356
Halkbank	0.7589
Vakıfbank	0.7445
Denizbank	0.7362
QNB Finansbank	0.7501
Şekerbank	0.7258

Figure 7. *The coherence score versus the number of topics for 10 Banks.*



In the quest to distill coherent topics from the voluminous data set of user reviews, a meticulous coherence analysis was performed for each banking app independently shown in Figure 7. The analysis was operationalized through the implementation of the Latent Dirichlet Allocation (LDA) algorithm, with the coherence scores serving as the benchmark for topic quality. Each subplot in the collective display corresponds to a unique banking application, wherein the coherence scores are plotted against a spectrum of topic quantities. This graphical representation elucidates the point at which the coherence score reaches its zenith, thereby signaling the most salient number of topics for the app in question. The coherence score, a quantifiable measure of topic relevance, peaks at an optimal number, which is indicative of the most meaningful and distinct thematic groupings that the LDA model can uncover from the data. This exploratory phase is pivotal, as it sets the stage for a more granular thematic analysis, ultimately enhancing the interpretability and applicability of the findings within the domain of customer feedback analytics.

Figure 8. *Word clouds for two topics across ten mobile banking apps*

The visual representation (shown in figure 8) provided by the word clouds offers an intuitive grasp of the prevalent themes within the corpus of Turkish mobile banking app reviews. In these word clouds, each term's textual dimension is proportional to its frequency across the reviews, offering immediate insight into the most salient topics discussed by users. These graphic illustrations encapsulate the essence of two distinct topics per banking application, with each bank's individual subplot foregrounding the most prominent terms in the Turkish language. Such graphical synopses not only shed light on the key concerns and features that customers frequently mention but also underscore the linguistic nuances inherent in the customer feedback. This analytical approach facilitates a user-centric understanding of the data, allowing for a nuanced interpretation of consumer sentiments and preferences within the digital banking landscape in Turkey. Through this lens, the word clouds serve as a catalyst for more in-depth qualitative analysis, guiding stakeholders to pinpoint specific areas of user experience that may require attention or commendation.

6. Discussion

This study offers insights into customer dissatisfaction with mobile banking applications in Turkey, pivoting on the question: "If consumers are satisfied with digital banking services, why are there persistent low ratings?". Despite the tendency for ratings to reflect the general sentiment of users, a more nuanced examination of user comments reveals inconsistencies. The analysis showed that ratings of 3, ostensibly neutral, frequently harbored a latent positive or negative bias, underscoring a divergence between the numerical rating and the textual sentiment. These findings are exemplified in the discrepancies highlighted by the sentiment analysis, where this machine learning models, including advanced algorithms like BERT, achieved up to 95% accuracy in classification.

Temporal trends in user feedback, captured graphically, disclosed patterns and periods of heightened negative sentiment, particularly following app updates, underscoring the urgency for robust testing and quality assurance post-deployment. Topic modeling unveiled recurrent themes across different banks, with certain issues emerging episodically, linked to app stability post-updates, and others persisting over time, such as user interface grievances.

The manifestation of these protracted issues suggests a shortfall in the banking management's response to software glitches and user experience shortcomings. The insights derived from this research underscore the imperative for banks to engage skilled personnel for software troubleshooting and to prioritize customer feedback in the continuous improvement of their mobile applications. The persistent nature of some complaints indicates that investments in timely and adequate resolutions have been lacking, leading to sustained user frustration and the potential attrition of clientele. This study provides a scaffold for banking institutions to identify and rectify customer issues proactively, thereby fostering loyalty and trust in their digital services.

7. Conclusion

The purpose of this study was to unravel the underlying factors contributing to user dissatisfaction with mobile banking applications in Turkey. Despite banks' efforts to maintain a sterling reputation among their clientele, there are instances where this goal falls short. We analyzed textual reviews from prominent Turkish mobile banking applications available on the Google Play Store, categorizing them by sentiment. The study scrutinized any inconsistencies between the star ratings and the derived sentiments of the reviews.

The analysis of mobile banking app reviews through advanced text mining techniques has yielded significant insights into customer satisfaction and service quality in the context of Turkish banks. The findings reveal a nuanced interplay between customer expectations and app performance, with a discernable impact on the overall sentiment reflected in the reviews. The coherence of topics extracted from these reviews underscores the critical areas of focus for banks, namely app functionality, security, user experience, and responsiveness to customer feedback. The accuracy of sentiment analysis algorithms, enhanced by machine learning models such as Random Forest, Gradient Boosting Machine, and BERT, further validates the reliability of these insights, emphasizing their potential to guide improvements in mobile banking services.

Conclusively, the sentiment and trend analysis over time indicates that banks must prioritize continuous app testing and updates to address user-reported issues promptly. As the negative sentiment often correlates with app updates and functionality issues, there is an imperative for banks to engage in meticulous software development and user interface design to enhance customer satisfaction. The consistent attention to customer feedback, as reflected in the periodic trends of reviews, can lead banks not only to rectify current shortcomings but also to preemptively refine their digital offerings. By harnessing the power of big data analytics, banks can pivot towards a more customer-centric approach, thereby fostering loyalty and trust in the increasingly competitive arena of digital banking.

The findings revealed distinct periods where the volume of negative reviews eclipsed positive ones. These periods of intensified criticism were then dissected using the LDA model to pinpoint prevailing issues, with each application exhibiting two dominant topics. The essence of these topics was captured in word clouds, succinctly summarizing the primary concerns.

A recurrent theme across many banking applications was the emergence of issues following software updates, suggesting a potential oversight in pre-release testing. This negligence often resulted in unstable app versions, eliciting a barrage of customer complaints. Moreover, inaccuracies in transaction details and a lack of timely resolutions to functional and nonfunctional flaws have eroded trust in these institutions. Users also expressed dissatisfaction with the user interface design and sluggish transaction processing.

Importantly, the feedback indicates that customers are generally aware of the necessary enhancements to the applications and are prepared to continue using the services, conditional on these improvements. This juncture presents a critical opportunity for banks to address the identified shortcomings, thereby restoring and preserving customer satisfaction. In conclusion, this research not only sheds light on the specific areas of mobile banking that require attention but also emphasizes the importance of vigilant software maintenance and customer-centric service design in the competitive landscape of digital banking.

Broadening the scope to include a comparative analysis of mobile banking app reviews from different regions and languages to gain a more comprehensive understanding of user satisfaction and service quality on a global scale. Additionally, longitudinal studies could track changes in customer sentiment over time, especially in response to technological advancements, economic shifts, and evolving user expectations. Further investigation into the impact of specific app features, such as biometric security or AI-driven customer service, on overall user experience could yield deeper insights. There is also a rich opportunity to explore the intersection of sentiment analysis with behavioral data to predict customer retention and churn. Machine learning models could be refined to enhance the precision of sentiment classification, and the integration of image and emoji analysis could provide a more holistic view of user feedback. Finally, future studies could also look into the role of social media platforms in shaping user perceptions and expectations of mobile banking services.

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