alphanumeric
https://alphanumericjournal.com/

Volume 13
Issue 02
Year 2025

Research Article

Evaluation of the effect of mobile applications on corporate reputation with artificial intelligence through user comments: E-Government case

Mehmet Kayakuş [1] & Dilşad Erdoğan [2]

[1] Assoc. Prof., Department of Business Information Systems, Manavgat Faculty of Social and Human Sciences, Akdeniz University, Antalya, Türkiye
[2] Lect., Department of Finance, Korkuteli Vocational School, Akdeniz University, Antalya, Türkiye

Abstract

This study examines the impact of e-government mobile applications on corporate reputation through user comments. Today, when digitalisation is accelerating, public services offered through mobile applications directly affect user experiences and shape the reputation of institutions. 2000 user comments from the Google Play Store were analysed using artificial intelligence methods, text mining, and sentiment analysis techniques. It was determined that 45% of the comments were positive, 15% were negative, and 40% were neutral. Positive comments indicate that the application has a positive user perception in general. However, some users were dissatisfied due to technical problems. As a result of text mining, the most frequently mentioned words and phrases of users were analysed, and feedback was categorised through sentiment analysis. In this process, WordNet was used to extract word frequencies, TextBlob was applied to classify user comments into positive, negative, and neutral categories, and Seaborn visualisations such as word clouds were employed to illustrate the findings. The findings reveal the importance of mobile applications for the sustainability of digital public services. It is emphasised that the technical performance of the application should be improved to increase user satisfaction and strengthen institutional reputation.

Keywords Corporate reputation, Mobile application, E-government, Artificial intelligence

Jel Codes C80, C88, H10

Contents

2025.13.02.MIS.01

Correspondence

M. Kayakuş
mehmetkayakus@akdeniz.edu.tr

Timeline

Submitted	Jun 04, 2025
Revision Requested	Oct 10, 2025
Last Revision Received	Oct 10, 2025
Accepted	Nov 05, 2025
Published	Dec 31, 2025

Citation

Kayakuş, M. & Erdoğan, D. (2025). Evaluation of the effect of mobile applications on corporate reputation with artificial intelligence through user comments: E-Government case, *alphanumeric journal*, 13 (2), 37-54. https://doi.org/10.17093/alphanumeric.1713959

ORCID

M. Kayakuş 0000-0003-0394-5862
D. Erdoğan 0000-0002-9117-5994

1. Introduction

In today's world, where digitalisation is rapidly spreading, the provision of public services in an electronic environment stands out as an important transformation that facilitates individuals' daily lives. In this process, e-government applications enable citizens to access public services quickly, reliably and efficiently, bringing the interaction between the state and citizens to a digital level. Launched in Türkiye in 2008, the e-Government Portal is at the heart of digital public services and, with its growing user base, has become a platform that facilitates citizens' access to public services. The mobile application of this platform, with its large user base and the convenience it offers, stands out as an important part of the digital transformation.

This has also affected the perception of institutions providing these services among citizens and their corporate reputation. Digital platforms provide an important source for evaluating feedback by enabling users to express their satisfaction and experiences in real time. In this context, comments from e-government mobile application users are a critical indicator that measures not only user satisfaction but also the perceived reliability and effectiveness of public institutions.

The starting point of this study is the limited number of studies in the literature aimed at understanding the effects of e-government mobile applications on user experience and corporate reputation and the need for more insight on this subject. The role of user feedback in the sustainability of public services and digitalisation processes is gaining increasing importance in the existing literature, but studies in this area specific to Türkiye remain limited.

The aim of this study is to analyse the feedback of individuals using the e-Government mobile application in Türkiye to examine the perception of the application among users and how this perception reflects on the corporate reputation of public institutions. 2,000 user reviews obtained from the Google Play platform were analysed using artificial intelligence techniques, and the strengths and weaknesses of the application were evaluated based on these reviews. The study offers a comprehensive approach to understanding how user feedback can be interpreted in the digitalisation process of public services, using advanced methods such as sentiment analysis and text mining. In this context, this study aims to provide critical insights not only into the performance of the e-Government application but also into the sustainability of digital public services and the perception of public institutions among citizens. This study makes significant contributions to the limited literature on the e-government mobile application in Türkiye and offers guiding recommendations for the development of digital public services.

In this context, the central research question of the study is formulated as follows: "How is the distribution of positive and negative user reviews on the e-Government mobile application related to indicators of corporate reputation?" Based on this question, the main hypothesis (H1) is defined as: "Positive user feedback on the e-Government mobile application has a significant positive association with the perceived corporate reputation of public institutions, while negative feedback undermines this perception." To test this hypothesis, artificial intelligence-based text mining and sentiment analysis techniques were employed. Specifically, WordNet was used for keyword frequency extraction, TextBlob was applied for sentiment classification, and Seaborn visualisation tools were utilised to represent the findings. This methodological approach provides a structured way to quantify the relationship between user feedback and institutional reputation in the digital public service context.

2. Literature

Reputation is an important factor that affects the long-term success of an organisation, expressing how it is perceived by its stakeholders (Fombrun & Riel, 2004). Institutional reputation is shaped by factors such as the quality of an organisation's services, its reliability and its contribution to social responsibility projects (Dowling, 2006). Having a good reputation offers advantages such as increasing customer loyalty, strengthening investor confidence, and making the organisation more resilient in times of crisis. However, corporate reputation is influenced not only by internal factors but also by external factors such as media, public opinion, and feedback on digital platforms (Chun, 2005).

Recent studies indicate that in the digital age, corporate reputation is shaped by dynamic data such as user feedback and social media interactions. For example, Dijkmans et al. (2015) found that positive user comments on social media directly increase corporate reputation, while negative comments have a detrimental effect. In this context, analysing user comments on digital platforms provides a powerful method for understanding corporate reputation. User reviews are among the critical factors that shape the reputation of an organisation or brand, as positive feedback can increase brand credibility, while negative comments may damage it (Fombrun, 1996; Moon, 2002).

In addition, recent research has directly linked e-government services to the reputation of public institutions. Al Ali et al. (2023), for instance, show that user experiences with government e-services in the UAE significantly influence perceptions of institutional reputation, underlining the importance of service quality and trust in shaping public image.

Digitalisation is transforming citizens' interactions with the state by increasing the accessibility of public services (Heeks, 2006). E-government systems enable individuals to save time, access services more quickly, and increase transparency by providing public services electronically (Carter & Bélanger, 2005). In Türkiye, the e-Government Portal launched in 2008 has since reached a wide user base through mobile applications. Mobile applications are effective tools that facilitate access to public services, and studies emphasise that these technologies play a critical role in building trust in government (Ojo et al., 2013).

However, the literature also shows that mobile applications present challenges in terms of technical infrastructure and user experience (Melin et al., 2016). Technical issues in particular emerge as a barrier to adoption (Rana et al., 2013). The sustainability of digital platforms such as e-Government is therefore not only related to the quality-of-service delivery but also to continuous improvement based on technical performance and user feedback. Studies in Türkiye have revealed both the potential benefits and limitations of e-government applications (Alkan & Ünver, 2020; Dede, 2024; Naralan, 2010; Tosun, 2024; Çankaya Kurnaz, 2024). These works collectively point to the importance of trust, usability, and institutional adaptation for successful digital transformation.

Recent studies have also emphasised the growing role of AI in enhancing the quality and efficiency of e-government services. For example, Al-Besher & Kumar (2022) highlight how artificial intelligence can improve service delivery and user interaction in public platforms. Similarly, Vrabie (2023) proposes an "E-Government 3.0" model, demonstrating how AI-driven approaches contribute to the development of more democratic and citizen-focused local administrations.

In recent years, artificial intelligence and natural language processing (NLP) techniques have been increasingly applied to analyse user feedback. Tools such as WordNet and TextBlob provide effective results in tasks such as word frequency extraction and sentiment classification (Loria et al., 2014; Miller, 1995). Seaborn and Word Cloud visualisations further enhance the presentation of results (Heimerl et al., 2014; Waskom, 2021).

Sentiment analysis, as highlighted by Pang & Lee (2008) and Liu (2012), is widely used to identify positive, negative, and neutral tendencies in text. Studies in Türkiye also show that such techniques provide insights into how citizens perceive e-government services and highlight the role of technical performance in shaping satisfaction (Alkan & Ünver, 2020; Gupta & Mathur, 2024). Moreover, comparative works indicate that AI-based approaches not only improve analytical accuracy but also support decision-makers in enhancing user satisfaction and corporate reputation (Castilla et al., 2023; Hakimi et al., 2023; Kavut, 2024).

3. Materials and Methods

This study aims to analyse user reviews of the e-Government mobile application using artificial intelligence techniques. In line with the main aim of the study, several sub-objectives have been identified to provide a more systematic framework for the analysis. First, the study seeks to identify the distribution of positive, negative, and neutral sentiments in user reviews of the e-Government mobile application. Secondly, it aims to determine the most frequently mentioned words and themes in these reviews by applying text mining techniques. Another objective is to examine how technical performance issues, such as errors, crashes, or difficulties in access, affect users' satisfaction and perceptions. In addition, the study focuses on evaluating the relationship between user feedback and the corporate reputation of public institutions, considering the extent to which digital experiences shape trust in government services. Finally, the study intends to contribute to the literature by demonstrating the applicability and effectiveness of AI-based sentiment analysis and text mining in the context of digital public services.

Research Questions:

- RQ1: What are the dominant sentiments (positive, negative, neutral) expressed by users in their reviews of the e-Government mobile application?
- RQ2: Which themes and keywords are most frequently mentioned by users, and how do they reflect satisfaction or dissatisfaction?
- RQ3: How do technical problems and usability issues influence the perception of the application?
- RQ4: In what ways does user feedback on the mobile application affect the corporate reputation of public institutions?

Within the scope of the study, a total of 2,000 user reviews of the e-Government mobile application were collected from the Google Play Store. The Python programming language and related libraries were used to collect the data. In the text mining and sentiment analysis processes, Python's WordNet library was used to determine the frequency of keywords and terms in user reviews. The TextBlob library was preferred for sentiment analysis; this library was used as an effective tool for classifying emotional tendencies (positive, negative, neutral) in user reviews. Additionally, the Seaborn library was used to create word clouds for the visualisation of the obtained data. These visualisations provide a general overview of the application's user experiences and satisfaction. The analysis process of the study revealed the effects of user comments on the brand and corporate reputation of the e-government mobile application through an in-depth examination of user comments.

3.1. Data set

The e-government mobile application was selected as an example for this study. The data set was compiled from user reviews of the e-government application on Google Play. The reviews were collected over a specific period, covering the timeframe from January 2023 to June 2024. This period was chosen to include the most recent user experiences and to ensure that seasonal or event-based factors, such as application updates or changes in public service demand, could be reflected in the dataset. Clearly defining the data collection timeframe also allows for a more transparent interpretation of the findings by taking into account potential temporal effects on user feedback. There are several reasons for choosing Google Play. First, Google Play is one of the largest mobile application platforms with a wide user base worldwide, and the reviews on it are a valuable source of data reflecting the experiences and opinions of application users. In addition, reviews on Google Play are generally detailed and include various user perspectives, providing a rich and comprehensive data set for the analysis process.

The selection of 2,000 reviews as the data set was determined to ensure the reliability and validity of the data analysis. 2,000 reviews provide a sufficiently large data set for statistical analysis while also ensuring that the analysis process remains manageable. As a result, sentiment analysis and text mining performed on the data set produce more meaningful and generalisable results. Additionally, this number of reviews provides sufficient diversity to cover feedback from different user segments of the application. Table 1 contains information about the e-government application on Google Play.

Table 1. E-government Google Play information

Features	E-government
Number of downloads	50 million+
Number of reviews	205.000
Rating	4.1
Release date	14.05.2015
Size	18 MB
Required Android version	5.0 and above

Source: GooglePlay (2024)

Table 1 shows that the e-Government application has a large user base, with over 50 million downloads, indicating that the application is widely used and preferred by many users. The fact that there are 205,000 reviews indicates that the application has been significantly evaluated by its users and that user experiences are widely shared. This high number of reviews indicates that the application provides a rich data set for collecting and analysing user feedback. The application has an average rating of 4.1. This indicates that users generally evaluate the app positively, but that there are also areas for improvement. A rating of 4.1 out of 5 implies that the app is quite successful in terms of user satisfaction but that it is open to further development to meet all user needs. An example data set is provided in Table 2.

Table 2. Sample data set

Emotional State	Comments
Negative	I can't access the app anymore; it keeps giving me an error message.
	When I log in, I can't do anything and the app closes.
Neutral	It's progressing well, I hope it continues to develop.
	Hello, the application is very good, but I've been having problems lately.
Positive	There are many useful applications that save time.
	The collection of information belonging to public institutions under one roof and easy access to many documents makes it very easy for us.

Source: GooglePlay (2024)

3.2. Text mining

Text mining is a set of techniques used to extract meaningful information from unstructured text data. These techniques are based on natural language processing (NLP), statistics, and machine learning methods. Today, text mining is widely used in the analysis of large data sources such as social media, customer feedback, news articles, and user comments (Feldman & Sanger, 2006).

Text mining typically consists of several stages. In the first stage, the data pre-processing process is carried out. In the preprocessing phase, the Python programming language was used together with several NLP libraries. Specifically, the NLTK toolkit was applied for tokenisation and stop-word removal, while SnowballStemmer and WordNetLemmatizer were used for stemming and lemmatisation processes. These tools ensured that the words were standardised into their root forms, thereby improving the accuracy of subsequent sentiment analysis. In addition, all text data were converted to lowercase and stripped of punctuation marks using Python's built-in string processing functions. In this stage, texts are cleaned, stop words are removed, stemming or root analysis is performed, and texts are brought into a more suitable structure for analysis (Aggarwal, 2012). This process reduces noise in the texts and makes the content to be analysed more meaningful.

In the second stage, the text vectorisation method is applied. This means converting texts into numerical data. One of the most used methods is the TF-IDF (Term Frequency-Inverse Document Frequency) method. TF-IDF is used to determine how often a word appears in a document and whether that word is specific to that document (Ramos, 2003)

Information extraction in text mining involves analysing frequently used words, term frequencies and word patterns. N-gram analysis is a method frequently used for this purpose. N-grams are groups of words in a text arranged in a specific order. The most used form is unigram (single word) analysis; however, bigram and trigram analyses are also used to examine the frequency of words used together (Schonlau et al., 2017).

Text mining is applied in many different fields. Analysing customer reviews in the e-commerce sector enables valuable insights to be gained for brands from user feedback (Liu, 2012). It is also used in social media data and news analysis in various fields such as public opinion, trend analysis and sentiment analysis (Blei et al., 2003).

Advancements in artificial intelligence and deep learning techniques in recent years have made text mining more powerful. Deep learning models such as BERT (Bidirectional Encoder Representations from Transformers) have the capacity to analyse the meaning of texts more deeply and successfully capture contextual meanings (Nam et al., 2022).

Text mining is a powerful method for converting unstructured data into meaningful information. Today, it is frequently used in many industries, particularly in areas such as big data analytics, social media monitoring, customer feedback analysis, and sentiment analysis (Kayakuş & Yiğit Açıkgöz, 2023). With the advancement of technology and artificial intelligence methods, it is anticipated that text mining will continue to evolve and expand into broader application areas.

3.3. Emotion analysis

Sentiment analysis is a natural language processing (NLP) technique used to classify the emotional content of texts and identify emotional tendencies (positive, negative, neutral) from this content. It is widely used to understand the emotional tone of large text data sets such as social media comments, customer feedback, and news articles (Pang & Lee, 2008). The primary goal of sentiment analysis is to automatically classify the emotional tendencies expressed in texts. This classification is typically based on positive, negative, or neutral categories. Today, sentiment analysis is frequently used in e-commerce, social media, and user review analysis (Liu, 2012). In the context of this study, sentiment analysis was performed with the TextBlob library to assign polarity scores to each review. Reviews with scores greater than zero were classified as positive, less than zero as negative, and equal to zero as neutral. This categorisation enabled a quantitative distribution of user sentiments, which was further visualised with Seaborn. Separate word clouds were also generated for each sentiment group to highlight the dominant terms within positive, negative, and neutral feedback.

The methods used in sentiment analysis are generally divided into two categories: rule-based methods and machine learning-based methods. Rule-based methods rely on predefined dictionaries and grammatical rules. In this method, words are classified based on their meanings in specific sentiment dictionaries (Taboada et al., 2011). For example, certain words are labelled as positive or negative, and these labels are used to determine the overall sentiment of the text.

In machine learning-based methods, texts are automatically classified based on a specific training data set. This method generally yields more successful results in more complex and dynamic text data sets (Pang & Lee, 2008). Deep learning models analyse the meaning of texts contextually, classifying words not only based on their individual meanings but also on their usage context within sentences (Liu, 2012).

Sentiment analysis has a wide range of applications in many different fields. It is particularly used in marketing and business to analyse customer reviews and measure brand perception (Ravi & Ravi, 2015). For example, analysing user reviews of a mobile application can help understand how users perceive it. This analysis provides important insights for the development of a product or service (Gebauer et al., 2007).

Additionally, the analysis of social media data is another important application area of sentiment analysis. On social media platforms, users can provide positive or negative feedback about a brand, product, or service. Analysing this feedback enables brands to increase customer satisfaction and intervene in potential crisis situations in advance (Thelwall et al., 2012).

Sentiment analysis is an important tool for automatically analysing the emotional content of large text data sets. Combined with machine learning and natural language processing techniques, this method provides valuable insights in areas such as marketing, social media and user feedback. With the development of technology and artificial intelligence algorithms, sentiment analysis methods are expected to become even more advanced and spread to wider areas of application.

3.4. Corporate Reputation and Mobile Application

Corporate reputation is the sum of the perception and reputation of an organisation in the eyes of its stakeholders. This reputation is shaped by factors such as the quality of services provided by an organisation to society, transparency in business processes, reliability, commitment to ethical values, contribution to social responsibility projects and sustainability (Dowling, 2006). Corporate reputation is evaluated not only by financial success but also by its capacity to respond to societal expectations. A high corporate reputation can increase customer loyalty, strengthen investor confidence and contribute to employee engagement (Fombrun & Riel, 2004). However, reputation protection depends on both internal and external factors. With the rapid spread of technology and digitalisation, digital tools such as mobile applications play an important role in shaping corporate reputation.

The impact of mobile applications on corporate reputation is evaluated based on factors such as user experience, app functionality, ease of use and customer support. A mobile app can increase user satisfaction by making an organisation's services easily accessible. For example, mobile applications of public institutions can increase the speed and quality of the services they provide to citizens, contributing to the strengthening of public trust in the public sector and thus corporate reputation. Rapid feedback received through mobile applications allows organisations to improve their services more effectively, which has a positive impact on reputation (Sucu, 2022). However, technical problems in mobile applications can cause user dissatisfaction and have a negative impact on corporate reputation. Therefore, regular updates of mobile applications and continuous improvement of the user experience are critical for maintaining a positive corporate image.

In conclusion, mobile applications have become an important component of corporate reputation in the digital age. Organizations' interaction with users through mobile applications can positively or negatively affect their reputation. Therefore, by continuously improving their mobile applications and paying attention to user feedback, organizations can have the opportunity to protect and strengthen their reputation in the long term (Kim & Lennon, 2013).

4. Results

In the initial phase of the study, the texts constituting the data set were subjected to preprocessing within the scope of natural language processing (NLP). Text preprocessing involves a series of steps aimed at removing noise and unnecessary information from the raw data and making it suitable for analysis (Yıldırım & Yıldız, 2018). In the first stage, "noise removal" was performed, which removes meaningless or unwanted elements from the texts.

The next step, tokenisation, allows the text to be broken down into smaller chunks, i.e., tokens, making it possible to analyse the text data in more detail. The text normalisation process was carried out to transform the words into a standard form, and at this stage, operations such as stemming, lemmatisation, case conversions, and removal of meaningless words were applied (Yılmaz & Yumuşak, 2021)

Stemming refers to the process of removing affixes (prefixes and suffixes) from the texts to reveal word roots, while lemmatisation ensures that words are reduced to root form by considering the morphological structure of the language (Özdemir & Türkoğlu, 2022). In addition, removing words that do not contribute to the overall meaning of the text is also one of the preprocessing stages, and in this process, meaningless or unnecessary words are removed.

In this study, the TextBlob library was used to perform sentiment analysis of user comments. TextBlob is a widely used library in Python that performs natural language processing (NLP) tasks in a simple way (Loria et al., 2014). It provides an effective way to identify key features of texts, such as sentiment analysis, linguistic polarity and subjectivity. TextBlob performs these tasks by classifying whether sentences in texts are positive, negative or neutral and by measuring the intensity of these emotions.

TextBlob performs sentiment analysis using a rule-based approach. In this approach, texts are analysed based on predefined rules and lexicon-based methods. In the background of TextBlob, a large dictionary of word sentiment is available to determine the emotional polarity of words in texts. Each word is assigned a positive, negative or neutral value, and an overall result is obtained by calculating the total sentiment value of all words in the text. Positive values represent a positive sentiment of the text, while negative values represent a negative sentiment. Neutral values indicate cases where the text contains no emotion (Sri et al., 2019). TextBlob also determines how personal or objective the text is with the "subjectivity" score. This approach reveals not only the emotional tone of the text but also the extent to which it reflects individuals' personal views (Ahuja & Dubey, 2017).

TextBlob was chosen for this study because it provides a fast and effective categorisation of the sentiments obtained from user comments. The sentiment analysis provided by TextBlob is not limited to determining whether the comments are positive, negative or neutral but also allows for a more detailed analysis of the users' overall perception and satisfaction level with the application. In particular, the rule-based approach allows for a more precise sentiment classification of the texts, which contributes to a more accurate interpretation of the data obtained in the study.

Table 3 shows the sentiment statistics of the comments on the e-Government application.

Table 3. Emotion state statistics

Emotion Status	Number of Comments
Positive	910
Negative	300
Neutral	800

When the sentiment distribution of e-government mobile application users' comments in Table 3 is analysed, it is seen that 45.3% of the comments are positive, 14.9% are negative and 39.8% are neutral. These findings show that users are generally satisfied with the application and have a positive perception. The high rate of positive comments indicates that users are largely satisfied with the services provided by the app and that the app has a positive impact on the brand and corporate reputation. On the other hand, 14.9% of negative comments indicate that some users are dissatisfied with certain features or experiences. The 39.8% of neutral comments indicate that a significant proportion of users were neither positive nor negative about the app and therefore did not express overall satisfaction or discomfort. This distribution indicates that the app offers a generally positive user experience, although there is room for improvement.

In addition to frequency and percentage distributions, statistical tests were applied to validate the robustness of the findings. A Chi-square test was conducted to examine whether the differences among positive, negative, and neutral sentiment categories were statistically significant. The results indicated that the distribution of sentiments was not random but significantly different across categories ($p < 0.01$), confirming that positive feedback dominated the dataset. Furthermore, correlation analysis was performed between user ratings on Google Play and sentiment categories. A moderate positive correlation ($r \approx 0.45$) was observed between higher user ratings and positive sentiment classifications, suggesting that users who provided higher scores also tended to express positive textual feedback. These additional statistical analyses strengthen the evidence that user satisfaction, as reflected in both ratings and comments, contributes to shaping the corporate reputation of public institutions.

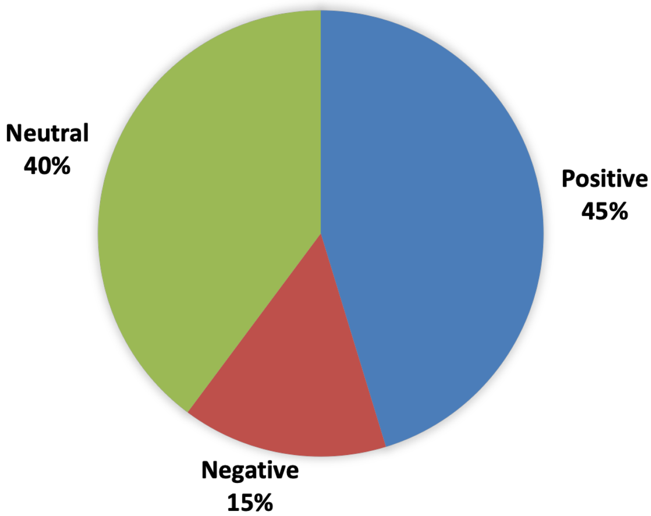

Figure 1. Graphical representation of sentiment distribution

It is seen that 45% of user comments are positive. This indicates that the app is generally positively evaluated by users and that the overall satisfaction level is high. On the other hand, 15% negative comments indicate that the app has room for improvement for some users. These users may have had negative experiences with the app, or their expectations may not have been met. It is seen that 40% of the comments are neutral, meaning that these users do not express a clear positive or negative opinion about the app. These neutral reviews may indicate that the app did not evoke a particular emotion or created ambivalence in users. In general, although the proportion of positive reviews is high, there is a significant proportion of neutral and negative reviews, suggesting that the app may have some areas that need improvement. While this distribution has a positive impact on the corporate reputation of the app, it also indicates that the app needs to be improved to meet the needs of some user segments.

Table 4 shows the word frequency list created from the most frequently mentioned words in the comments.

Table 4. Word Frequency List

Positive	Negative	Neutral
Nice	Error	Application
Recommendation	Problem	Process
Improvement	Not Working	Time
Acknowledgements	Closing	State
Useful	Trouble	Update

The word frequency list, which is based on comments about the e-Government application on Google Play, provides important insights into users' experiences. When the most prominent words in the list are analysed, it becomes clear that users' experiences are largely negative. Words such as "error", "problem", "Not working", " closing ", and "trouble" reveal that the app frequently encounters technical problems, leaving users dissatisfied. Conversely, positive feedback such as "nice", "recommendation", "improvement", "acknowledgements", and "useful" is less frequent in the list. This suggests that while some users had positive experiences, the general user base complained about technical glitches. Words in the neutral category, such as "application", "process", "time", "state", and "update", indicate that users focus on the application's basic functions and its ability to provide access to e-government services. However, this process needs improvement. Overall, these results indicate serious user concerns about the technical performance of the e-government application, suggesting a need for more comprehensive technical improvements and user experience optimisation.

In the study, visualisations for the analysis of user comments were performed using the Seaborn library, one of the powerful data visualisation tools of the Python programming language. Seaborn is a preferred library, especially for presenting statistical data in a more understandable and aesthetic way (Sial et al., 2021). This library offers advanced visualisation techniques to effectively present patterns, distributions and relationships of data. The main reason for choosing Seaborn in the study is to make the data obtained from user comments more easily understandable and comparable.

Word Cloud was used to present the frequency and distribution of the words obtained in the text mining and sentiment analysis processes. Word clouds are a technique that allows visualisation of the most repeated words in texts with size and colour differences (Heimerl et al., 2014). This technique is particularly effective in identifying the most frequently mentioned words from user comments and visually emphasising them. By providing a visual summary of keywords in text, word clouds enable quick analysis of large data sets and help to understand which topics are most frequently mentioned by users (Viegas et al., 2009).

The reason for using the word cloud in this study is to reveal which features or functions of the e-government mobile application received the most feedback by highlighting the terms that users use most frequently in their comments. Thus, it was made visually tangible which aspects of the application were highlighted by the users and which areas needed improvement. Seaborn and WordCloud, when used together, provide an effective method for summarising text data and visually presenting user perception. Figure 2 shows the word cloud formed from user comments.

Figure 2. Word cloud of positive comments

The word cloud in Figure 2 reflects the overall impression of positive user comments on the e-Government application. Users consider the application to be useful, functional and a tool that facilitates access to public services. Although technical problems are occasionally mentioned in the comments, it is understood that these problems have been resolved, and the application has been improved through updates. In addition, citizens see the application as a practical solution that allows them to quickly carry out their daily transactions. Overall, users are satisfied with the e-government application and support digital access to public services. Words such as “useful”, “recommendation” and “acknowledgements” highlight the functional and practical value of the application, directly supporting the dimension of service quality in corporate reputation. Similarly, terms like “nice” and “improvement” indicate satisfaction with continuous development, representing innovation and responsiveness, which strengthen the perception of institutional reliability.

Figure 3. Word cloud of negative comments

The word cloud in Figure 3 reveals the prevalence of negative user experiences with the e-Government application. Users report that the application has technical problems and that there are difficulties in accessing and logging in. Incompatibility with mobile devices, frequent closing of the application and errors during transactions are among the most prominent complaints. In addition, some users express their dissatisfaction by stating that such problems have been going on for a long time and no solution has been produced. In general, technical glitches and deficiencies in the user experience form the basis of the negative perception of the app. Negative words such as "error", "problem", "not working" and "trouble" directly undermine the technical reliability and trustworthiness dimensions of corporate reputation. Frequent mentions of system failures and access difficulties point to weaknesses in the usability and stability of the service. These deficiencies reduce citizens'

Figure 4. Word cloud of neutral comments

The word cloud in Figure 4 reflects the main problems that stand out in negative user comments about the e-government application. Users mostly complain about problems in accessing the application, inability to log in and technical errors. The fact that the application does not open, frequently gives errors and is incompatible with mobile devices negatively affects the user experience. Moreover, the fact that some transactions are not resolved for a long time or the system is unstable undermines citizens' trust in digital services. This situation points to the need to make the application more stable and user-friendly. Neutral words such as "application", "process", "time" and "update" generally reflect the accessibility and continuity dimensions of digital services. Although these terms are not emotionally charged, they indicate users' expectations of stability and performance. The repeated reference to "update" in particular shows that citizens link the application's improvements to the institution's ability to provide sustainable and reliable digital services, an important element of long-term corporate reputation.

5. Discussion

This analysis of user comments on the e-government mobile application reveals important results on the technical difficulties encountered in the provision of digital public services and the effects of these services on user experience. In addition, studies show that mobile government services have an important impact on the institutional reputation of the state by facilitating access to public services provided by the state. The findings of the study suggest that mobile applications play a key role in providing digital access to public services, but such services need to be continuously improved in terms of technical performance and user satisfaction. In this discussion section, the results will be compared with similar studies in the literature, and conclusions will be drawn about the general success criteria of e-government applications.

e-Government applications are generally considered in the literature as tools that have the potential to increase the speed and efficiency of digital government services. The success of e-government applications is directly related to users' trust in and continuous use of these services (Carter &

Bélanger, 2005). In this context, the findings of our study show that users frequently criticise the application for technical problems, confirming concerns that this may undermine trust in digital public services. Bugs, crashes and functionality issues were the main reasons for user dissatisfaction. As noted in other studies, technical performance and reliability are critical factors for the adoption of eGovernment applications (Melin et al., 2016). To address these concerns, states need to strengthen their legal and technical infrastructure to provide more reliable and efficient services to citizens using AI & IoT-based systems. In this context, the diversity of services should be increased, and advanced digital services should be provided by making services more reliable and accessible with artificial intelligence, big data analytics, and blockchain technologies (Yürük & Öztaş, 2017).

According to the data obtained in study, 45.3% of user comments were classified as positive, 14.9% as negative and 39.8% as neutral. This distribution shows that, in general, users have a positive attitude towards the purpose of the application, but that technical glitches overshadow these positive experiences. Especially the intensification of complaints about technical performance is considered a critical issue for the sustainability of digital public services in the existing literature (Bertot et al., 2010). The sustainability of digital services and their widespread adoption among users depends not only on the functionality of the services but also on the continuity and reliability of the service. In the literature, it is stated that users' trust in digital services is directly related to the continuity and error-free delivery of these services (Shareef et al., 2011). In this context, technical problems such as cybersecurity, data privacy and transparency that users may encounter should be solved (Ateş & Yavuz, 2019).

Another important factor determining the success of e-government applications is whether these applications are user-friendly. The findings of our study show that user comments indicating that the interface of the application is simple and understandable have a positive impact. For example, users emphasised user-friendly features with comments such as "The app's menus are easy to access" and "I can quickly complete the process I need". However, some users expressed difficulties due to technical issues and complex instructions, especially at certain stages of the transactions. For example, statements such as "Some of the processes have too many steps and are confusing" and "I struggle a lot to find the document I want" point to areas where the user experience needs to be improved. These results show that a user-friendly design is critical for the adoption and effectiveness of e-government applications. If users find the application complex or their transactions challenging, this may decrease the usage rates of the application. Although the findings of our study indicate that some users recommend the application and that the application should be improved, the low technical performance limits the impact of these positive comments. Previous studies have also emphasised that e-government applications should offer user-friendly interfaces and that ease of access to digital services plays an important role in the adoption of the application (Venkatesh et al., 2012). User-friendly designs and ease of operations increase overall satisfaction by enabling users to use digital services effectively. In the mobile application development process, user feedback is a critical resource for continuous understanding of the system. The E-Government Gateway application in Türkiye should be updated regularly to spread the user experience, and more attention can be paid to user feedback (Naghizade et al., 2018). For this reason, it is thought that analysing negative comments can help improve government services and strengthen trust relationships.

There is also a need to focus more on the technical infrastructure and digital transformation process of e-government applications. Technical problems are recognised as one of the biggest obstacles to the expansion of digital public services (Rana et al., 2013). Application crashes or functionality issues can not only negatively affect individual user experiences but also undermine the efficiency of public services. Therefore, the technical infrastructure of platforms providing digital public services needs to be made more resilient and responsive to user feedback. In addition to technical infrastructure services, training and practices to increase the level of digital literacy, cybersecurity and data privacy, and the adaptation process of public employees should be improved (Çelen et al., 2011). This finding is also frequently emphasised in the literature; the sustainability of digital services depends not only on technical innovations but also on continuous maintenance and improvement processes (Gupta et al., 2016).

The findings of this study support the existing literature focusing on the technical performance of e-government applications and user satisfaction. Successful delivery of digital public services requires continuous updating and improvement of applications to ensure that users have confidence in the services. In this context, the results of our study reveal the need for technical improvements in terms of sustainability of e-government applications and user satisfaction. It is thought that increasing the performance of the application with technological support, especially by taking user feedback into account, is effective in achieving success in the digital transformation process of e-government services.

6. Conclusion

In this study, user comments on the e-Government mobile application, which provides access to Türkiye's digital public services, were analysed using text mining and sentiment analysis techniques. The 2000 user comments collected from the Google Play Store were analysed using the Python programming language and various libraries (WordNet and TextBlob), and the prominent keywords and emotional tendencies were identified. The aim of the study is to gain a deeper understanding of the user experiences of the e-Government mobile application and to identify the strengths and weaknesses of the application based on these comments. The findings show that there are various problems in the technical performance of the application and that users have provided serious feedback on these issues.

It was determined that 45.3% of the user comments were positive, 14.9% were negative and 39.8% were neutral. Although this distribution shows that users generally find the app positive, it also indicates that the app faces a serious technical problem. The word cloud analysis clearly reveals that the most frequent themes in users' experiences are technical problems. The frequent repetition of words such as "error", "problem", "not working", "shutting down" and "trouble" indicates that the app has not fully met user expectations in terms of stability and performance.

The findings of this study show that the e-government mobile application plays an important role in digital transformation processes but that various technical challenges are encountered in this process. The data obtained from user comments reveal that although the application has received positive feedback in general, important steps need to be taken to improve the user experience. Making the app more stable, making performance improvements and solving technical problems encountered by users will increase overall user satisfaction. It is also recommended that regular updates should be made by taking user feedback into account and that necessary training and information activities should be carried out to enable users to use the application more effectively.

Successful delivery of digital public services will be possible not only by strengthening the technical infrastructure of the application but also by continuously monitoring and improving the user experience. Accordingly, e-government mobile applications can provide more effective and efficient services to a wider audience with technical improvements and user-orientated developments.

Declarations

Conflict of interest The author(s) have no competing interests to declare that are relevant to the content of this article.

References

Aggarwal, C. C. (2012). Mining Text Streams. In *Mining Text Data* (pp. 297–321). Springer US. https://doi.org/10.1007/978-1-4614-3223-4_9

Ahuja, S., & Dubey, G. (2017). Clustering and sentiment analysis on Twitter data. *2017 2nd International Conference on Telecommunication and Networks (TEL-NET)*, 1–5. https://doi.org/10.1109/tel-net.2017.8343568

Al Ali, F., Stephens, M., & Pereira, V. (2023). Government e-Services and Reputation. In *Doing Business in the Middle East* (pp. 235–252). Routledge. https://doi.org/10.4324/9781003005766-19

Al-Besher, A., & Kumar, K. (2022). Use of artificial intelligence to enhance e-government services. *Measurement: Sensors*, *24*, 100484. https://doi.org/10.1016/j.measen.2022.100484

Alkan, Ö., & Ünver, Ş. (2020). Türkiye'de E-Devlet Hizmetlerinin Kullanımını Etkileyen Faktörlerin Analizi. *Atatürk Üniversitesi İktisadi Ve İdari Bilimler Dergisi*. https://doi.org/10.16951/atauniiibd.757571

Ateş, H., & Yavuz, Ö. (2019). Elektronik Devletten Mobil Devlete Geçiş: Fırsatlar, Tehditler ve Uygulama Örnekleri. *Bilgi Ekonomisi Ve Yönetimi Dergisi*, *14*(2), 155–177.

Bertot, J. C., Jaeger, P. T., & Grimes, J. M. (2010). Using ICTs to create a culture of transparency: E-government and social media as openness and anti-corruption tools for societies. *Government Information Quarterly*, *27*(3), 264–271. https://doi.org/10.1016/j.giq.2010.03.001

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, *3*, 993–1022.

Carter, L., & Bélanger, F. (2005). The utilization of e-government services: citizen trust, innovation and acceptance factors*. *Information Systems Journal*, *15*(1), 5–25. https://doi.org/10.1111/j.1365-2575.2005.00183.x

Castilla, R., Pacheco, A., & Franco, J. (2023). Digital government: Mobile applications and their impact on access to public information. *Softwarex*, *22*, 101382. https://doi.org/10.1016/j.softx.2023.101382

Chun, R. (2005). Corporate reputation: Meaning and measurement. *International Journal of Management Reviews*, *7*(2), 91–109. https://doi.org/10.1111/j.1468-2370.2005.00109.x

Dede, A. (2024). Dijital vatandaşlığın dokuz boyutu ve e-devlet uygulamaları. *EKEV Akademi Dergisi*, *97*, 15–27. https://doi.org/10.17753/sosekev.1365162

Dijkmans, C., Kerkhof, P., & Beukeboom, C. J. (2015). A stage to engage: Social media use and corporate reputation. *Tourism Management*, *47*, 58–67. https://doi.org/10.1016/j.tourman.2014.09.005

Dowling, G. (2006). Reputation risk: it is the board's ultimate responsibility. *Journal of Business Strategy*, *27*(2), 59–68. https://doi.org/10.1108/02756660610650055

Feldman, R., & Sanger, J. (2006). *The Text Mining Handbook: Advanced Approaches in Analyzing Unstructured Data*. Cambridge University Press. https://doi.org/10.1017/cbo9780511546914

Fombrun, C. J. (1996). *Reputation: Realizing Value from the Corporate Image*. Harvard Business School Press.

Fombrun, C. J., & Riel, C. B. M. v. (2004). *Fame & fortune: how successful companies build winning reputations*. Pearson Education.

Gebauer, J., Tang, Y., & Baimai, C. (2007). User requirements of mobile technology: results from a content analysis of user reviews. *Information Systems and E-Business Management*, *6*(4), 361–384. https://doi.org/10.1007/s10257-007-0074-9

GooglePlay. (2024). *E-Devlet Kapısı*. https://play.google.com/store/apps/details?id=tr.gov.turkiye.edevlet.kapisi&hl=tr

Gupta, K. P., Singh, S., & Bhaskar, P. (2016). Citizen adoption of e-government: a literature review and conceptual framework. *Electronic Government, An International Journal*, *12*(2), 160. https://doi.org/10.1504/eg.2016.076134

Gupta, S., & Mathur, N. (2024). *User-centred exploration of m-governance adoption: identifying and analysing determinants*. *18*. https://doi.org/10.1108/TG-01-2024-0027

Hakimi, M., Salem, M. H., Miskinyar, M. S., & Sazish, B. (2023). Integrating Artificial Intelligence into E-Government: Navigating Challenges, Opportunities, and Policy Implications. *International Journal of Academic and Practical Research*, *2*(2), 11–21.

Heeks, R. (2006). *Implementing and Managing eGovernment: An International Text*. SAGE Publications Ltd. https://doi.org/10.4135/9781446220191

Heimerl, F., Lohmann, S., Lange, S., & Ertl, T. (2014). Word Cloud Explorer: Text Analytics Based on Word Clouds. *2014 47th Hawaii International Conference on System Sciences*, 1833–1842. https://doi.org/10.1109/hicss.2014.231

Kavut, S. (2024). Toplumların Dijital Dönüşüm Aracı Olarak Yapay Zekâ Çalışmaları: Türkiye'nin ve Türk Devletleri Teşkilatının Yapay Zekâ Kullanımı Üzerine Bir Analiz. *Erciyes İletişim Dergisi*, *11*(1), 325–344. https://doi.org/10.17680/erciyesiletisim.1346576

Kayakuş, M., & Yiğit Açıkgöz, F. (2023). Twitter'da Makine Öğrenmesi Yöntemleriyle Sahte Haber Tespiti. *Abant Sosyal Bilimler Dergisi*, *23*(2), 1017–1027. https://doi.org/10.11616/asbi.1266179

Kim, J., & Lennon, S. J. (2013). Effects of reputation and website quality on online consumers' emotion, perceived risk and purchase intention: Based on the stimulus-organism-response model. *Journal of Research in Interactive Marketing*, *7*(1), 33–56. https://doi.org/10.1108/17505931311316734

Liu, B. (2012). *Sentiment Analysis and Opinion Mining* (1st ed. 2012). Springer International Publishing.

Loria, S., Keen, P., Honnibal, M., Yankovsky, R., Karesh, D., & Dempsey, E. (2014,). *Textblob: Simplified Text Processing*. https://textblob.readthedocs.io/en/dev/

Melin, U., Axelsson, K., & Söderström, F. (2016). Managing the development of e-ID in a public e-service context: Challenges and path dependencies from a life-cycle perspective. *Transforming Government: People, Process and Policy*, *10*(1), 72–98. https://doi.org/10.1108/tg-11-2013-0046

Miller, G. A. (1995). WordNet: a lexical database for English. *Communications of the ACM*, *38*(11), 39–41. https://doi.org/10.1145/219717.219748

Moon, M. J. (2002). The Evolution of E-Government among Municipalities: Rhetoric or Reality?. *Public Administration Review*, *62*(4), 424–433. https://doi.org/10.1111/0033-3352.00196

Naghizade, K., Karakethüdaoğlu, M., & Akbiyik, A. (2018,). Mobil Uygulama Geliştirmede Geri Bildirimin Önemi: Türkiye E-Devlet Örneği. *International Congress on Economics and Business 2018*.

Nam, W., Lee, J., & Jang, B.-C. (2022). Text summarization of dialogue based on BERT. *Journal of the Korea Society of Computer and Information*, *27*(8), 41–47. https://doi.org/10.9708/jksci.2022.27.08.041

Naralan, A. (2010). E-Devlet'e Etki Eden Faktörler. *Atatürk Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, *12*(2), 457–468.

Ojo, A., Janowski, T., & Awotwi, J. (2013). Enabling development through governance and mobile technology. *Government Information Quarterly*, *30*, S32–S45. https://doi.org/10.1016/j.giq.2012.10.004

Pang, B., & Lee, L. (2008). Opinion Mining and Sentiment Analysis. *Foundations and Trends® in Information Retrieval*, *2*(1–2), 1–135. https://doi.org/10.1561/1500000011

Ramos, J. E. (2003). Using TF-IDF to Determine Word Relevance in Document Queries. *Proceedings of the First Instructional Conference on Machine Learning*, 133–142. https://api.semanticscholar.org/CorpusID:14638345

Rana, N. P., Dwivedi, Y. K., & Williams, M. D. (2013). Analysing challenges, barriers and CSF of egov adoption. *Transforming Government: People, Process and Policy*, *7*(2), 177–198. https://doi.org/10.1108/17506161311325350

Ravi, K., & Ravi, V. (2015). A survey on opinion mining and sentiment analysis: Tasks, approaches and applications. *Knowledge-Based Systems*, *89*, 14–46. https://doi.org/10.1016/j.knosys.2015.06.015

Schonlau, M., Guenther, N., & Sucholutsky, I. (2017). Text Mining with n-gram Variables. *The Stata Journal: Promoting Communications on Statistics and Stata*, *17*(4), 866–881. https://doi.org/10.1177/1536867x1801700406

Shareef, M. A., Kumar, V., Kumar, U., & Dwivedi, Y. K. (2011). e-Government Adoption Model (GAM): Differing service maturity levels. *Government Information Quarterly*, *28*(1), 17–35. https://doi.org/10.1016/j.giq.2010.05.006

Sial, A. H., Rashdi, S. Y. S., & Khan, A. H. (2021). *International Journal of Advanced Trends in Computer Science and Engineering*, *10*(1), 277–281. https://doi.org/10.30534/ijatcse/2021/391012021

Sri, V. R., Niharika, C., Maneesh, K., & Ismail, D. M. (2019). Sentiment Analysis of Patients' Opinions in Healthcare using Lexicon-based Method. *International Journal of Engineering and Advanced Technology*, *9*(1), 6977–6981. https://doi.org/10.35940/ijeat.a2141.109119

Sucu, İ. (2022). Kurumsal Sosyal Sorumluluk Kampanyalarının Marka İmajına Etkisi: Turkcell Markası Örneği. *Yalova Sosyal Bilimler Dergisi*, *12*(2), 140–147.

Taboada, M., Brooke, J., Tofiloski, M., Voll, K., & Stede, M. (2011). Lexicon-Based Methods for Sentiment Analysis. *Computational Linguistics*, *37*(2), 267–307. https://doi.org/10.1162/coli_a_00049

Thelwall, M., Buckley, K., & Paltoglou, G. (2012). Sentiment strength detection for the social web. *Journal of the American Society for Information Science and Technology*, *63*(1), 163–173. https://doi.org/10.1002/asi.21662

Tosun, A. (2024). Kamu Yönetiminde Hizmet Sunumunda Bir Paradigma Değişimi: E-Devlet. *International Journal of Social Sciences*, *8*(33), 137–154. https://doi.org/10.52096/usbd8.33.10

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology1. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.2307/41410412

Viegas, F., Wattenberg, M., & Feinberg, J. (2009). Participatory Visualization with Wordle. *IEEE Transactions on Visualization and Computer Graphics*, *15*(6), 1137–1144. https://doi.org/10.1109/tvcg.2009.171

Vrabie, C. (2023). E-Government 3.0: An AI Model to Use for Enhanced Local Democracies. *Sustainability*, *15*(12), 9572. https://doi.org/10.3390/su15129572

Waskom, M. (2021). seaborn: statistical data visualization. *Journal of Open Source Software*, *6*(60), 3021. https://doi.org/10.21105/joss.03021

Yürük, E., & Öztaş, N. (2017). E-Devlet Ana Kapıları Üzerine İnceleme: Türkiye ve Seçilmiş Ülkeler. *Süleyman Demirel Üniversitesi İktisadi Ve İdari Bilimler Fakültesi Dergisi*, *22*(Kayfor 15 Özel Sayısı), 2133–2157.

Yıldırım, S., & Yıldız, T. (2018). Türkçe için karşılaştırmalı metin sınıflandırma analizi. *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*, *24*(5), 879–886.

Yılmaz, H., & Yumuşak, S. (2021). Açık Kaynak Doğal Dil İşleme Kütüphaneleri. *İstanbul Sabahattin Zaim Üniversitesi Fen Bilimleri Enstitüsü Dergisi*, *3*(1), 81–85. https://doi.org/10.47769/izufbed.879217

Çankaya Kurnaz, S. (2024). Türkiye'nin e-devlet olgunluk düzeyi: BM e-devlet gelişmişlik endeksi üzerinden bir değerlendirme. *Yönetim Bilimleri Dergisi*. https://doi.org/10.35408/comuybd.1513698

Çelen, F. K., Çelik, A., & Seferoğlu, S. S. (2011). Türkiye'deki e-Devlet Uygulamalarının Değerlendirilmesi. *XIII. Akademik Bilişim Konferansı Bildirileri*, 59–67.

Özdemir, E., & Türkoğlu, İ. (2022). Yazılım Güvenlik Açıklarının Evrişimsel Sinir Ağları (CNN) ile Sınıflandırılması. *Fırat Üniversitesi Mühendislik Bilimleri Dergisi*, *34*(2), 517–529. https://doi.org/10.35234/fumbd.1076870