alphanumeric
https://alphanumericjournal.com/
Volume 12
Issue 02
Year 2024

Research Article

Evaluating of the Impact of Ministry of Health Mobile Applications on Corporate Reputation Through User Comments Using Artificial Intelligence

Mehmet Kayakuş [1]

[1] Manavgat Faculty of Social and Human Sciences, Akdeniz University, Antalya, Türkiye

Abstract

In this study, the impact of mobile applications developed by the Ministry of Health of the Republic of Turkey as part of its digitalization strategy on corporate reputation is analysed by using artificial intelligence methods through user comments. Within the scope of the research, the last 300 user comments of MHRS, Hayat Eve Sığar and eNabız applications on Google Play were analysed, and sentiment analysis and text mining techniques were applied. The findings reveal that MHRS and eNabız applications are generally perceived positively by users, which has a positive impact on the corporate reputation of the Ministry of Health. 81% of MHRS users and 73% of eNabız users made positive comments about the applications. However, for the Hayat Eve Sığar application, the positive comment rate remained at 51 percent, and more technical problems were reported. This shows that the application offers complex user experiences and needs to be improved. In conclusion, it is emphasized that the mobile applications of the Ministry of Health have strengthened its corporate reputation in general, but user satisfaction and sustainability of technical performance are critical to maintaining this reputation.

Keywords Mobile application, Corporate reputation, Ministry of Health, Artificial intelligence, Sentiment analysis, Text mining

Jel Codes I10, G34, S46

Contents

2024.12.02.MIS.01

Correspondence

M. Kayakuş
mehmetkayakus@akdeniz.edu.tr

Timeline

Submitted	Aug 22, 2024
Revision Requested	Nov 20, 2024
Last Revision Received	Nov 20, 2024
Accepted	Dec 04, 2024
Published	Dec 31, 2024

Citation

Kayakuş, M. (2024). Evaluating of the Impact of Ministry of Health Mobile Applications on Corporate Reputation Through User Comments Using Artificial Intelligence, *alphanumeric*, 12 (2), 59-74. https://doi.org/10.17093/alphanumeric.1537174

1. Introduction

The Ministry of Health develops various digital tools and applications to improve the efficiency and quality of healthcare services across the country. These efforts aim to increase the accessibility and efficiency of healthcare services and enable citizens to access health information faster and more easily (Qiang et al., 2011). Mobile applications play an important role in this context; they make access to health services, information, and management processes more efficient. The mobile applications of the Ministry of Health stand out as a critical tool to better meet the needs of users regarding healthcare services and to be the pioneer of digital transformation in the healthcare sector (Latif et al., 2017).

Corporate reputation refers to the image and reliability of an organization in the eyes of society, and this reputation is directly related to user experience and satisfaction (Nguyen & Leblanc, 2001). The impact of the Ministry of Health's mobile applications on its corporate reputation is directly related to the effectiveness, user-friendliness, and value provided by these applications. The quality of mobile applications and users' satisfaction with these applications have a significant impact on the overall reputation of the organization. Therefore, evaluation and continuous improvement of the applications are essential for strengthening organizational reputation (McCuiston & DeLucenay, 2010).

User reviews provide valuable information about the performance and user experience of mobile applications (Weichbroth & Baj-Rogowska, 2019). The comments shared by users about applications provide important data to understand the strengths and weaknesses of the application. These comments play a critical role in determining to what extent the application meets the needs of users and in which areas it requires improvement. Therefore, systematic analysis of user comments can make significant contributions to the development of mobile applications (Genc-Nayebi & Abran, 2017).

Artificial intelligence is a powerful tool for analysing large data sets and drawing meaningful conclusions (Brynjolfsson & Mcafee, 2017). The use of artificial intelligence technologies in analysing user comments enables faster and more accurate processing of the information obtained from these comments. Sentiment analysis, topic modelling and other artificial intelligence techniques can be used to understand users' feelings and tendencies about the application. This approach enables the creation of more data-driven and effective strategies in corporate reputation management and mobile application development processes (Provost & Fawcett, 2013).

In this study, the impact of the mobile applications of the Ministry of Health on corporate reputation will be analysed by using artificial intelligence through user comments. This study will make an important contribution both to better understand the effects of digital applications on corporate reputation in the health sector and to reveal the potential of artificial intelligence applications in such analyses.

Mostafa (2013)'s study utilised text mining methodologies to explore latent trends in consumer sentiments regarding international brands. A random subset comprising 3516 tweets was employed to evaluate consumer attitudes towards prominent brands such as Nokia, T-Mobile, IBM, KLM, and DHL. The findings suggest that organisations can adeptly leverage the blogosphere to revamp their marketing and promotional strategies. Furthermore, the research indicates that Twitter serves as a dependable platform for analysing perceptions of global brands.

Kang & Park (2014) have developed a novel framework for gauging customer satisfaction with mobile services by leveraging sentiment analysis and VIKOR to assess customer reviews. The framework is primarily comprised of two key phases: data collection and preprocessing and customer satisfaction measurement. During the data collection and preprocessing phase, text mining is employed to assemble attribute and sentiment word dictionaries derived from the review data. Subsequently, sentiment analysis is utilised to compute the sentiment scores of attributes for each mobile service. In the customer satisfaction measurement stage, a sentiment score matrix is constructed, and the overall customer satisfaction is determined by taking into account various attributes using VIKOR.

Peng & Wan (2023) developed a new system for evaluating corporate image. They first established the system by conducting a literature review. Then, they analysed online public information using a dictionary-based topic classification and sentiment analysis algorithm. The accuracy of this algorithm was then assessed, and the results demonstrated the effectiveness of the corporate image evaluation method.

Loke & Pathak (2023) have developed a Decision Support System (DSS) designed to aid organisations in appraising the corporate reputation (CR) of their brands through the aggregation of feedback pertaining to their products and services and the derivation of cutting-edge key performance indicators. The system harnesses machine learning (ML) text classification models that are trained and validated across diverse sources, using real-time data streams from platforms specialised in user reviews, such as Trustpilot. Additionally, it has been assessed using previously unobserved comments gathered from public company pages and channels on social networking platforms like Facebook. Notably, the Naive Bayes model demonstrated the highest level of performance based on the F1 score metric.

In assessing the impact of mobile health apps on organisational reputation, this study provides a specific context for such apps. Previous research has generally evaluated health apps in terms of the quality of healthcare services or user satisfaction. By analysing app reviews in detail, this study aims to reveal the concrete effects of the Ministry of Health's digital strategies and app performance on corporate reputation. It also highlights the potential of artificial intelligence applications in the healthcare sector through in-depth analysis of user comments and offers a new perspective on how text mining and sentiment analysis techniques can be applied in this context. In these aspects, the study provides a new methodological approach to the evaluation of mobile applications in the healthcare sector and highlights the role of AI-based analyses in corporate reputation management, thus making a significant contribution to the literature in this field.

2. Material and Method

In this study, the effect of the mobile applications of the Ministry of Health of the Republic of Turkey on corporate reputation was analysed using artificial intelligence methods through user comments, and the results were evaluated. The data set was obtained from the most recent 300 comments made by users on each mobile application on Google Play. Python programming language and sentiment analysis and text mining methods from artificial intelligence techniques were used to analyse user comments.

2.1. Dataset

The Ministry of Health has mobile applications to facilitate the work of citizens and healthcare professionals and to provide better service. Mobile applications are frequently preferred due to the ease of access from anywhere. The Ministry of Health has 40 mobile applications on Google Play (GooglePlay, 2024) and 33 mobile applications on App Store (AppStore, 2024). The applications can be downloaded and used free of charge by users for Android and iOS devices. In the study, it was preferred to examine Google Play applications. Analysing Google Play applications is a strategic choice in terms of inclusiveness and accessibility of the research. The Android operating system, as the most widely used platform in the global smartphone market, offers the opportunity to reach a wide and diverse user base. This makes it easier to analyse the effects of different demographic groups on app usage and to obtain generally valid findings. In addition, since the applications on the Google Play platform can be used on a wider range of devices and price ranges, the performance of these applications and their effects on user satisfaction can be evaluated more comprehensively. Therefore, examining Google Play applications will make a significant contribution to the study by increasing the generalisability of the findings of the study. Table 1 shows the Google Play information

Table 1. Google Play information of the Ministry of Health applications

Mobile app	Download Count	Comment Count	Score	Last Update Date
MHRS	10 Million+	312 B	4.8	45505
Hayat Eve Sığar	10 Million+	238 B	3.9	45196
eNabız	10 Million+	224 B	4.2	45511
Ekip	500 thousand+	1820	1.8	45280
ÜTS	500 thousand+	893	3	45512
112 Acil Yardım Butonu	100 thousand+	514	3.9	44238
İlaç Takip Sistemi (İTS)	100 thousand+	503	3.9	44825
Aşı Takip Sistemi	100 thousand+	1180	1.3	43236
Aşıla	100 thousand+	1190	2.5	45499
Özel Çocuklar Destek Sistemi	10 thousand+	30	3.5	44968
DYS	10 thousand+	110	3.6	45380
ESİM	10 thousand+	221	4.1	45267
Engelsiz Sesli Kitap	10 thousand+	32	3.8	42342
Dr. e-Nabız	10 thousand+	80	4.2	44228
Diyabet Kontrol Listeleri	5 thousand+	15	3.6	43446
Sporcu Sağlığı	5 thousand+	32	2.7	43676
Türkiye Beslenme Rehberi	5 thousand+	52	1.6	43448
Beyaz Kod	1 thousand+	19	3.2	43422
Gri Kod Acil Çağrı	1 thousand+	8	4.1	45267
Lifecare Mobil	1 thousand+	24	2.7	45518

Source: GooglePlay (2024)

The study was limited to the three most downloaded mobile applications of the Ministry of Health and Google Play due to the large number of data and the difficulty of interpretation. In the study, MHRS (Central Physician Appointment System), Hayat Eve Sığar and eNabız applications were examined. The MHRS (Central Physician Appointment System) mobile application allows citizens to make an appointment with the physician of their choice and on the appropriate date. E-Nabız is a mobile application through which citizens, their authorised relatives, and physicians can access personal health data collected from health facilities via the internet and mobile devices. Hayat Eve Sığar is a mobile application developed to inform and guide our citizens living within the borders of Turkey about the New Coronavirus (Covid-19) and to minimise the risks related to the epidemic that may occur and to prevent its spread. The mobile applications offered by the Ministry of Health in Table 1 have reached a wide user base on Google Play and have achieved high download numbers. The MHRS (Central Physician Appointment System) application has been downloaded over 10 million times and has been evaluated by users with a very high score (4.8). The application, which had 312 thousand comments in total, received its last update on 1 August 2024. Similarly, the Hayat Eve Sığar application was downloaded over 10 million times and received 238 thousand comments; however, this application was rated by users with a score of 3.9 and was last updated on 27 September 2023. eNabız application also reached over 10 million downloads, received 224 thousand comments, and left a positive impression in terms of user satisfaction with a score of 4.2. eNabız application was last updated on 7 August 2024 (GooglePlay, 2024). These data show that the MoH applications are actively used by large masses and that there are differences in user satisfaction.

The most recent 300 comments made by users on Google Play on the mobile applications of the Ministry of Health were analysed. Table 2 shows the sample data set.

Table 2. Sample data set

Mobile app	Comments	Sentiment State
MHRS	A very nice and easy application, it is very easy to make an appointment with the doctor you want	Positive
	I want to become a member, but the system gives an error and says there is no membership. I tried to become a member from the site, and the same problem appears again.	Negative
Hayat Eve Sığar	Installation is quite easy and works successfully. I congratulate you. It is a purposeful application.	Positive
	When I give location permission, the application crashes; when I do not give location permission, the map does not open.	Negative
eNabız	A nice application that contains all the health data that must be used in health issues together	Positive
	eNabız does not open every time I open the page. It refreshes but does not open	Negative

Source: GooglePlay (2024)

2.2. Text mining

Text mining is a data analysis method used to process, structure, and transform large amounts of textual data into meaningful information. This process combines natural language processing (NLP) and data mining techniques to discover patterns, relationships, trends, and meanings in texts (Kayakuş & Yiğit Açıkgöz, 2023). Text mining aims to gain insights by analysing unstructured or semi-structured text data and is used to examine different text types such as news articles, social media posts, user comments, and academic papers (Hippner & Rentzmann, 2006).

2.2.1. Text preprocessing

Text preprocessing is the first step to make raw data suitable for analysis. The raw text data is made analysed through processes such as cleaning, tokenization, and lemmatization.

In the cleaning stage, elements that do not carry meaning and that may negatively affect the analysis are removed from the commentary texts. These include punctuation marks, numbers, special characters, HTML tags, and common words known as stop words (e.g., ‘and’ ‘one’, ‘that’). Stop words are usually omitted from text analyses because they do not carry meaningful information (Grimmer & Stewart, 2013).

Tokenization allows each word or phrase to be treated as an independent unit. This stage makes it possible to segment the text for later analyses and to examine each token independently (Clark et al., 2022).

Lemmatization is the process of reducing words to the root form according to their grammatical structure. This process allows words that are used in different ways (e.g., ‘run’, ‘ran’, ‘ran’, ‘running’) to be reduced to a single root form (e.g., ‘run’), thus enabling a more consistent and meaningful analysis (Jivani, 2011).

2.2.2. Feature Extraction

In text mining, feature extraction refers to the process of systematically selecting specific features or patterns from texts to make raw text data processable and meaningful. This process is critical for discovering underlying meanings, themes, and relationships in text. Feature extraction occurs by reducing the text into smaller, numerically representable components, and these components form structures that can be used for analysis (Agrawal & Batra, 2013).

N-gram models provide basic structures that represent the features of texts by extracting consecutive groups of words in the text. Different types of n-grams, such as unigrams (one-word groups), bigrams (two-word groups), and trigrams (three-word groups), allow the analysis of grammatical structures and word relationships in text (Ogada et al., 2015). For example, the sentence ‘eNabız application is very useful’ is divided into groups such as ‘eNabız application’, ‘application is very useful’, ‘very useful’ with the bigram model. These groups are used to understand the connections between words and context.

2.2.3. Word Frequency Analysis

In the text mining process, word frequency analysis plays a critical role to determine the importance of words in the text (Pejić Bach et al., 2019). Term Frequency (TF) and Term Frequency-Inverse Document Frequency (TF-IDF) techniques are used for word frequency analysis (Addiga & Bagui, 2022).

Word frequency is a metric that measures the number of times a word occurs in each document or text. Word frequency helps to understand how important certain words are in the content of the text (Zhou & Slater, 2003). For example, words that occur frequently in user comments about an application may indicate which features or experiences users attach more importance to (O'Brien & Toms, 2008). A high TF value indicates that the word occurs frequently in the text and is therefore a meaningful component that can contribute to the analysis. Term Frequency-Inverse Document Frequency (TF-IDF) measures not only within a specific text but also by comparing it with other texts. This metric considers whether a word occurs frequently in a particular document but whether the same word is rare in other documents. In this way, words that are not common but important for that document are identified (Umadevi, 2020). This technique allows for a more in-depth analysis by increasing the importance of rare words in texts. For example, the word 'MHRS' may occur frequently in documents related to the Ministry of Health but may be rare in a general text collection. In this case, TF-IDF assigns this word a higher importance for that document.

2.3. Sentiment analysis

Sentiment analysis consists of a set of techniques and methods used in the process of detecting and classifying sentiment content in texts (Medhat et al., 2014). This process is performed using different approaches, and each approach offers certain advantages and disadvantages. The three main approaches are lexicon-based, machine learning-based, and hybrid approaches. These approaches use different methods and algorithms to improve the accuracy and efficiency of sentiment analysis (Elsaid Moussa et al., 2021).

The dictionary-based approach is a method that assigns predefined sentiment values to certain words or groups of words and uses these values to determine the sentiment tone of texts. The main component of this approach is a dictionary that determines whether words carry positive, negative, or neutral sentiment. The lexicons used in dictionary-based analysis usually contain sentiment scores for specific words (Nguyen & Huynh, 2022). For example, the word 'great' conveys a positive sentiment, while the word 'terrible' conveys a negative sentiment.

The advantages of the dictionary-based approach include the simplicity of its implementation and the ability to analyse quickly with existing word lists. However, this approach may struggle to capture context-dependent changes in the meaning of words. Also, it may not be able to recognise complex aspects of language, such as polysemous words or ironic expressions (Nguyen & Huynh, 2022). The machine learning-based approach uses supervised learning techniques to perform sentiment analysis. In this method, the model needs to be trained on a large data set to classify certain texts as positive, negative, or neutral. The training data consists of texts, each of which is assigned to a specific sentiment class, and the model performs the learning process on this data (Go et al., 2009).

The machine learning-based approach is more flexible than the dictionary-based approach as it can learn the meaning of words according to their context. This flexibility allows for polysemous words, irony, and context to be included in the analysis. Furthermore, by using various machine learning algorithms (such as Naive Bayes, Support Vector Machines, and LSTM), sentiment analysis can be made more complex and higher accuracy rates can be achieved (He et al., 2014). However, the major drawback of this approach is that it requires a large amount of labelled data to train the model, and these processes are time-consuming and computationally intensive.

The hybrid approach is a combination of lexicon-based and machine learning-based approaches. This approach aims to perform higher-accuracy sentiment analyses by combining the strengths of both methods. For example, a hybrid model uses a machine learning-based algorithm to perform basic sentiment classification, while a dictionary-based system can fine-tune words or provide extra information for highly significant words (Elsaid Moussa et al., 2021).

The major advantage of the hybrid approach is that it produces more robust and reliable results by balancing the shortcomings of both methods. Such a system combines the contextual analysis capabilities of a machine learning-based model with the specific word sentiment scoring capabilities of a dictionary-based system. However, the complexity of hybrid systems can make the development and implementation of such models more difficult and computationally intensive (Galar et al., 2012).

These three approaches are the main methods used in the sentiment analysis process. While dictionary-based approaches offer simplicity and speed, machine learning-based approaches provide flexibility and accuracy. Hybrid approaches offer a more advanced analysis by combining the advantages of both methods. Researchers and practitioners can choose one or a combination of these approaches depending on the type of data to be analysed, the resources available, and the desired level of accuracy.

3. Results and Discussion

Text preprocessing is the process of cleaning and structuring the raw data and is a fundamental step in making analyses more efficient and reliable. Text data often contains irregular and noisy components and needs to be processed appropriately to perform meaningful analyses. In this study, various preprocessing steps were applied to text data before starting advanced analyses such as data mining and sentiment analysis. Firstly, data cleaning was performed, and unnecessary characters, symbols, and noise (e.g., punctuation marks, numbers, special characters) were removed from the raw text. This step eliminated the effect of non-significant data in the analysis process, resulting in more accurate and reliable results. In addition, operations such as case normalisation (conversion of uppercase letters to lowercase letters) were also applied at this stage. Secondly, tokenisation was performed, and the texts were divided into smaller meaningful units (tokens), such as words or sentences. For example, the phrase 'MHRS application is very useful' is broken down into ['MHRS', 'application', 'very', 'useful']. Thirdly, stop words were removed from the texts. These words are frequently repeated words that usually do not make a significant contribution to the overall meaning of the text. The removal of words such as 'and', 'with', 'one', and 'this' from the texts helped the words that carry meaning to come to the fore in the analysis process. Finally, the lemmatisation process was applied, and the words were reduced to their root or basic forms (lemma). For example, the word 'running' was reduced to 'run'. This process increased the consistency in the analysis by ensuring that different forms of words have the same representation. In the lemmatisation process, the grammatical roots of the words were considered, resulting in a more meaningful data set. These preprocessing steps increased the accuracy and reliability of the study and contributed to the robustness and validity of the results obtained.

In this study, a rule-based approach is adopted for sentiment analysis, and the TextBlob library of the Python programming language is used. TextBlob is a library for performing text processing in a simple and intuitive way and is widely used for sentiment analysis. TextBlob's sentiment analysis function is based on word lists and predefined rules to evaluate the sentiment load of words and sentences in texts. This library classifies text as positive, negative, or neutral, producing a 'sentiment polarity' and 'attribution' score for each piece of text (Pandey et al., 2019). TextBlob's sentiment analysis feature calculates a polarity value according to whether the words in the text have a positive or negative meaning. This polarity value takes a value between −1 and +1; a value of −1 indicates a completely negative sentiment, while a value of +1 indicates a completely positive sentiment (Bonta et al., 2019). TextBlob also determines the degree of subjectivity of the text, which indicates how subjective or objective the text is. TextBlob's simple yet effective structure makes it a suitable tool for analysing the overall sentiment tone of user comments and assessing how corporate reputation is affected by them (Wan Min & Zulkarnain, 2020). Table 3 shows the sentiment statistics of user comments on the three most downloaded mobile applications of the Ministry of Health.

Table 3. The sentiment statistics

Mobile app	Positive	Negative	Neutral
MHRS	243	36	21
Hayat Eve Sığar	153	75	72
eNabız	219	51	30

When the percentage statistics related to the mood analysis of the user comments of MHRS, Hayat Eve Sığar and eNabız, the three most downloaded mobile applications of the Ministry of Health, are examined, it is seen that positive comments are generally dominant. The MHRS application shows that 81% of user comments are positive, 12% are negative, and 7% are neutral. This shows that the level of satisfaction with the MHRS application is quite high. eNabız application also shows a similar trend, with 73% of the comments being positive, 17% negative, and 10% neutral. On the other hand, the Hayat Eve Sığar application received a more diverse response in user comments, with 51% positive comments, 25% negative comments and 24% neutral comments. These data reveal that MHRS and eNabız applications are more successful in terms of user satisfaction, but the Hayat Eve Sığar application evokes more mixed feelings among users. Figure 1 shows the mood (positive, negative, neutral) distribution of the comments on the three mobile applications.

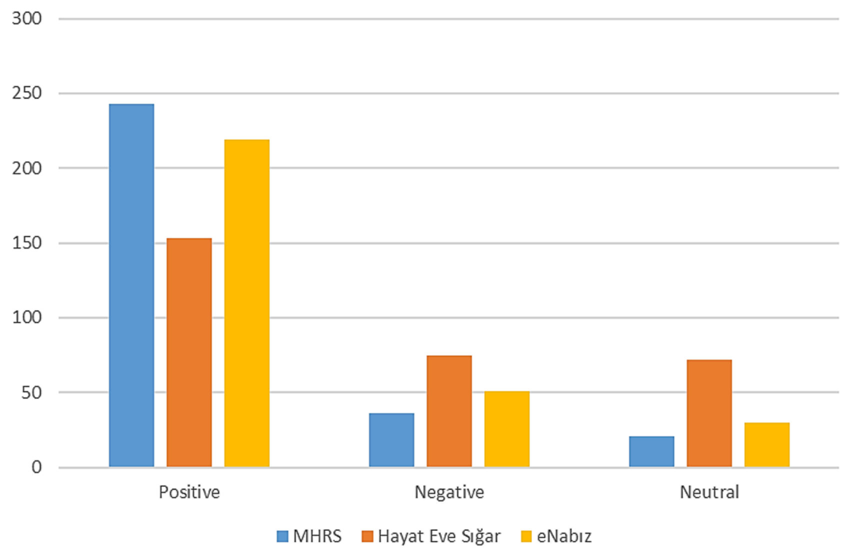

Figure 1. Sentiment distribution

Figure 1 shows the sentiment distribution of user comments for three mobile applications of the Ministry of Health (MHRS, Hayat Eve Sığar, eNabız). In the graph, it is seen that MHRS and eNabız applications largely received positive feedback, especially MHRS application reached the highest number of positive comments. On the other hand, the Hayat Eve Sığar (Life Fits in Home) application displayed higher rates of negative and neutral comments compared to the other two applications, leading to more mixed reactions among users. This distribution reveals that the applications show differences in terms of user satisfaction and perception.

In this study, Unigram (single word), one of the N-gram methods, was used in the text mining process. Unigram is a simple and effective method in which each word is treated as an independent unit. The reason why this method is preferred is the idea that the words in user comments can carry meaning on their own and can make significant contributions to the analysis results (Caropreso et al., 2001). The Unigram approach was used as an effective tool in determining the word frequencies in the text and conducting basic analyses. In this way, the most frequently used and prominent words in the texts were identified, and in-depth information was obtained about the general trends and content of user comments.

In this study, the Term Frequency-Inverse Document Frequency (TF-IDF) method, one of the information extraction techniques in the text mining process, is used. TF-IDF is a common and effective technique used to determine the importance of a word in a particular document. This method determines the contextual importance of a word by considering its frequency (TF) in a document and its rarity (IDF) in the overall document set. The reason why TF-IDF is preferred is that it reduces the impact of frequently used but contextually insignificant words and emphasises more meaningful and informative words (Huang et al., 2011). In this way, by identifying important words in user comments, more in-depth analyses could be made about the content of the texts. Table 4 shows the most frequently mentioned words in user comments on the three most downloaded mobile applications of the Ministry of Health.

Table 4. Word Frequency List

MHRS	Hayat Eve Sığar	eNabız
Appointment	Application	Application
Application	Telephone	Does not open
Convenient	Error	Update
Beautiful	Broken	The problem
No problem	Update	Not working
Fast	Resolved	It’s beautiful
Experienced	Acknowledgements	Health
Perfect	Slowly	Continuous
Convenience	Installation	Successful
Successful	Recommendation	Updated

Table 4 shows the most frequently used words in user comments for MHRS, Hayat Eve Sığar and eNabız, the three most downloaded mobile applications of the Ministry of Health. The most frequently used words for the MHRS application are ‘Appointment,’ ‘Convenient,’ ‘Nice,’ and ‘No problem,’ and these expressions show that the application is found functional and satisfactory by the users. For the Hayat Eve Sığar application, the most frequently used words were ‘Application,’ ‘Phone,’ and ‘Error,’ indicating that users frequently expressed feedback about technical problems and updates. The prominence of terms such as ‘Application,’ ‘Does not open,’ and ‘Update’ in the eNabız application indicates that users expressed that they had difficulties with the accessibility of the application and updates. These findings reveal that each application offers different user experiences and that these experiences are clearly reflected in user comments.

In this study, data visualisation was performed using the Seaborn library of the Python programming language. Seaborn is a powerful and flexible library designed to visualise statistical data. Seaborn Library was preferred to present the results of text mining and sentiment analysis on user comments in a more understandable and effective way (Waskom, 2021). This library allows visualisation of the distribution, associations, and patterns of the data, allowing the results of the analysis to be visualised (Sial et al., 2021).

In the study, word clouds were used to visualise word frequencies. Word cloud is a technique that visually represents the most frequently occurring words in texts and is presented in a dimensioned way according to the frequency of words. The word cloud allows to quickly identify keywords in the text and visually express the overall theme of the text (Hearst et al., 2020). The use of word clouds in this study allowed to easily identify prominent words and themes in user comments and contributed to a more effective visual presentation of the results obtained. The use of word clouds with the Seaborn library made it possible to present the data in a meaningful and aesthetic way and served to make the analysis findings more understandable and attractive. Figure 2 shows the word cloud of MHRS mobile application user comments.

Figure 2. Word cloud of MHRS mobile application user comments

In Figure 2, the most frequently mentioned words of user comments on the MHRS mobile application are visualised as a word cloud. In this visualisation, it is observed that words such as 'appointment,' 'application,' 'useful,' and 'nice' stand out. The prominent size of the word 'appointment' emphasises that the process of making an appointment, which is the main function of the application, is discussed intensively by the users and the central role of this process in the use of the application. In addition, positive descriptions such as 'useful' and 'nice' indicate a high level of user satisfaction. However, the presence of words such as 'error,' 'easy,' and 'system' in the word cloud indicates that technical details about the functionality of the application are also an important issue for users. This analysis reveals that the MHRS application is generally positively received by the users, but there is also some feedback about functionality and ease of use.

Figure 3 shows the word cloud of Hayat Eve Sığar mobile application user comments.

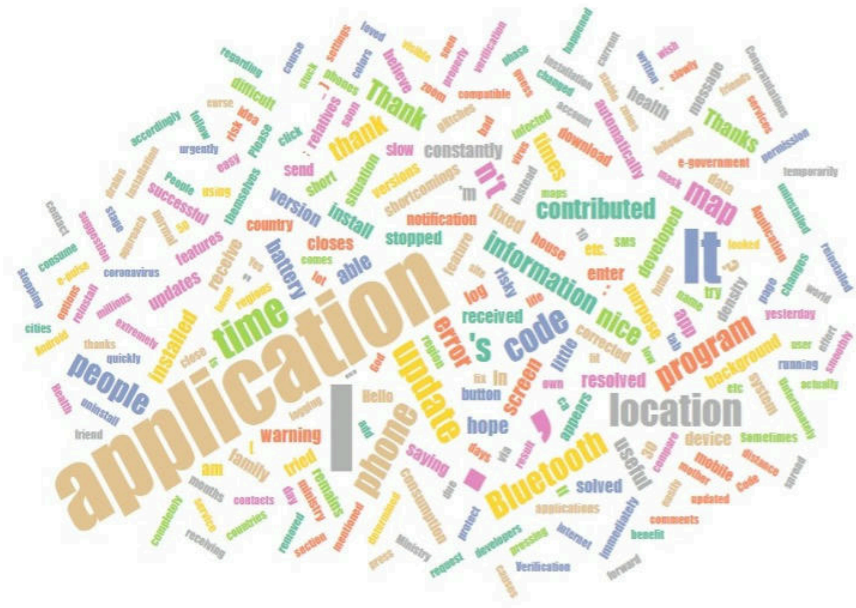

Figure 3. Word cloud of Hayat Eve Sığar mobile application user comments

In Figure 3, the most frequently mentioned words of the user comments on the Hayat Eve Sığar mobile application are visualised as a word cloud. In this visualisation, it is noteworthy that words such as 'application,' 'one,' 'very,' and 'for' are frequently used. The significant size of the word 'application' shows that users intensively express their experiences across the application. In addition, the frequent use of technical terms such as 'update,' 'error,' and 'not working' reflects user dissatisfaction with the technical performance of the application and updates. In addition, the presence of positive words such as 'thank you,' 'nice,' and 'health' indicates that the health-related functions of the application are appreciated, but users have mixed feelings about the overall functioning of the application. This word cloud reveals that there are significant technical problems in the user experience of Hayat Eve Sığar application and both positive and negative reactions to these problems.

Figure 4 shows the word cloud of eNabız mobile application user comments.

Figure 4. Word cloud of eNabız mobile application user comments

In the Figure 4, the most frequently mentioned words of user comments on the eNabız mobile application are visualised as a word cloud. In this word cloud, words such as 'application,' 'update,' 'information,' and 'time' stand out. The significant size of the words 'application' and 'update' shows that users focus on the update processes of the application and their experiences with updates. In particular, the frequent occurrence of technical terms such as 'log,' 'error,' and 'fixed' reveals that users expressed their difficulties with the application's performance and technical problems. In addition, the frequent use of the word 'information' emphasises the importance that users attach to the data and information they obtain from the application. In general, this word cloud shows that eNabız application is frequently evaluated by users in terms of technical performance and information access and that these processes have a significant impact on user satisfaction.

4. Conclusions

This study analyses the impact of MHRS, Hayat Eve Sığar, and eNabız—three of the most downloaded mobile applications developed by the Ministry of Health—on corporate reputation through user comments. By leveraging sentiment analysis and text mining techniques using Python programming, the study evaluates the extent to which this digital services influence user satisfaction and ultimately contribute to the Ministry's reputation.

The findings reveal that MHRS and eNabız have achieved remarkable success in fostering user satisfaction, thus positively influencing the Ministry's corporate reputation. Specifically, 81% of user comments about the MHRS application are positive, highlighting its functionality and user-friendly design. Similarly, 73% of comments for the eNabız application are positive, demonstrating that users value the reliability and importance of the health data provided. These results underscore the Ministry's achievements in digital service provision and how these applications enhance its reputation.

In contrast, user feedback on Hayat Eve Sığar (Life Fits in Home) reflects a broader spectrum of sentiments. While 51% of comments are positive, criticisms about technical issues and update processes indicate areas requiring attention. This suggests that although the application has been successful in certain aspects, unresolved challenges could potentially impact the Ministry's reputation negatively. The findings underscore the importance of sustainability and continuous improvement in digital services to maintain and enhance corporate reputation.

This study underscores the strategic role of mobile applications in the Ministry of Health's digital transformation efforts. To sustain and enhance its corporate reputation, the ministry should prioritize monitoring user feedback systematically, resolving technical issues promptly, and aligning updates with user needs. This proactive approach will not only strengthen user satisfaction but also solidify trust and credibility in the eyes of the public.

Future research could expand the scope of this analysis by comparing the Ministry's applications with those of other governmental or private health institutions to benchmark performance and identify best practices. Additionally, incorporating more advanced sentiment analysis models, such as deep learning-based approaches, could provide deeper insights into user emotions and preferences. Exploring the long-term impact of digital applications on health outcomes and public trust in governmental services could also contribute to understanding their broader societal implications.

In conclusion, the Ministry of Health's mobile applications serve as vital tools in its digital transformation journey. Their ongoing improvement and responsiveness to user needs will be instrumental in ensuring that the ministry continues to meet societal expectations and sustains its reputation in the digital era.

Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

References

Addiga, A., & Bagui, S. (2022). Sentiment Analysis on Twitter Data Using Term Frequency-Inverse Document Frequency. *Journal of Computer and Communications*, *10*(8), 117–128. https://doi.org/10.4236/jcc.2022.108008

Agrawal, R., & Batra, M. (2013). A detailed study on text mining techniques. *International Journal of Soft Computing and Engineering*, *2*(6), 118–121.

AppStore. (2024,). *Applications*. https://apps.apple.com/tr/developer/t-c-saglik-bakanligi/id867537600?l=tr

Bonta, V., Kumaresh, N., & Janardhan, N. (2019). A Comprehensive Study on Lexicon Based Approaches for Sentiment Analysis. *Asian Journal of Computer Science and Technology*, *8*(S2), 1–6. https://doi.org/10.51983/ajcst-2019.8.s2.2037

Brynjolfsson, E., & Mcafee, A. (2017). Artificial intelligence, for real. *Harvard Business Review*, *1*, 1–31.

Caropreso, M. F., Matwin, S., & Sebastiani, F. (2001). A learner-independent evaluation of the usefulness of statistical phrases for automated text categorization. *Text Databases and Document Management: Theory and Practice*, *5478*(4), 78–102.

Clark, J. H., Garrette, D., Turc, I., & Wieting, J. (2022). <scp>Canine</scp>: Pre-training an Efficient Tokenization-Free Encoder for Language Representation. *Transactions of the Association for Computational Linguistics*, *10*, 73–91. https://doi.org/10.1162/tacl_a_00448

Elsaid Moussa, M., Hussein Mohamed, E., & Hassan Haggag, M. (2021). Opinion mining: a hybrid framework based on lexicon and machine learning approaches. *International Journal of Computers and Applications*, *43*(8), 786–794. https://doi.org/10.1080/1206212x.2019.1615250

Galar, M., Fernandez, A., Barrenechea, E., Bustince, H., & Herrera, F. (2012). A Review on Ensembles for the Class Imbalance Problem: Bagging-, Boosting-, and Hybrid-Based Approaches. *IEEE Transactions on Systems, Man, And Cybernetics, Part C (Applications and Reviews)*, *42*(4), 463–484. https://doi.org/10.1109/tsmcc.2011.2161285

Genc-Nayebi, N., & Abran, A. (2017). A systematic literature review: Opinion mining studies from mobile app store user reviews. *Journal of Systems and Software*, *125*, 207–219. https://doi.org/10.1016/j.jss.2016.11.027

Go, A., Bhayani, R., & Huang, L. (2009). *Twitter sentiment classification using distant supervision* (Issue CS224N).

GooglePlay. (2024,). *Applications*. https://play.google.com/store/apps?hl=tr

Grimmer, J., & Stewart, B. M. (2013). Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts. *Political Analysis*, *21*(3), 267–297. https://doi.org/10.1093/pan/mps028

He, L., Yang, Z., Lin, H., & Li, Y. (2014). Drug name recognition in biomedical texts: a machine-learning-based method. *Drug Discovery Today*, *19*(5), 610–617. https://doi.org/10.1016/j.drudis.2013.10.006

Hearst, M. A., Pedersen, E., Patil, L., Lee, E., Laskowski, P., & Franconeri, S. (2020). An Evaluation of Semantically Grouped Word Cloud Designs. *IEEE Transactions on Visualization and Computer Graphics*, *26*(9), 2748–2761. https://doi.org/10.1109/tvcg.2019.2904683

Hippner, H., & Rentzmann, R. (2006). Text Mining. *Informatik-Spektrum*, *29*(4), 287–290. https://doi.org/10.1007/s00287-006-0091-y

Huang, C.-H., Yin, J., & Hou, F. (2011). A Text Similarity Measurement Combining Word Semantic Information with TF-IDF Method: A Text Similarity Measurement Combining Word Semantic Information with TF-IDF Method.

Chinese Journal of Computers, *34*(5), 856–864. https://doi.org/10.3724/sp.j.1016.2011.00856

Jivani, A. G. (2011). A comparative study of stemming algorithms. *Int. J. Comp. Tech. Appl.*, *2*(6), 1930–1938.

Kang, D., & Park, Y. (2014). Review-based measurement of customer satisfaction in mobile service: Sentiment analysis and VIKOR approach. *Expert Systems with Applications*, *41*(4), 1041–1050. https://doi.org/10.1016/j.eswa.2013.07.101

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

Latif, S., Rana, R., Qadir, J., Ali, A., Imran, M. A., & Younis, M. S. (2017). Mobile Health in the Developing World: Review of Literature and Lessons From a Case Study. *IEEE Access*, *5*, 11540–11556. https://doi.org/10.1109/access.2017.2710800

Loke, R., & Pathak, S. (2023). Decision Support System for Corporate Reputation Based Social Media Listening Using a Cross-Source Sentiment Analysis Engine. *Proceedings of the 12th International Conference on Data Science, Technology and Applications*, 559–567. https://doi.org/10.5220/0012136400003541

McCuiston, V. E., & DeLucenay, A. (2010). Organization Development Quality Improvement Process: Progress Energy's Continuous Business Excellence Initiative. *Journal of Business Case Studies (JBCS)*, *6*(6). https://doi.org/10.19030/jbcs.v6i6.255

Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, *5*(4), 1093–1113. https://doi.org/10.1016/j.asej.2014.04.011

Mostafa, M. M. (2013). More than words: Social networks' text mining for consumer brand sentiments. *Expert Systems with Applications*, *40*(10), 4241–4251. https://doi.org/10.1016/j.eswa.2013.01.019

Nguyen, B.-H., & Huynh, V.-N. (2022). Textual analysis and corporate bankruptcy: A financial dictionary-based sentiment approach. *Journal of the Operational Research Society*, *73*(1), 102–121. https://doi.org/10.1080/01605682.2020.1784049

Nguyen, N., & Leblanc, G. (2001). Corporate image and corporate reputation in customers' retention decisions in services. *Journal of Retailing and Consumer Services*, *8*(4), 227–236. https://doi.org/10.1016/s0969-6989(00)00029-1

O'Brien, H. L., & Toms, E. G. (2008). What is user engagement? A conceptual framework for defining user engagement with technology. *Journal of the American Society for Information Science and Technology*, *59*(6), 938–955. https://doi.org/10.1002/asi.20801

Ogada, K., Mwangi, W., & Cheruiyot, W. (2015). N-gram based text categorization method for improved data mining. *Journal of Information Engineering and Applications*, *5*(8), 35–43.

Pandey, M., Williams, R., Jindal, N., & Batra, A. (2019). Sentiment analysis using lexicon based approach. *IITM Journal of Management and IT*, *10*(1), 68–76.

Pejić Bach, M., Krstić, Ž., Seljan, S., & Turulja, L. (2019). Text Mining for Big Data Analysis in Financial Sector: A Literature Review. *Sustainability*, *11*(5), 1277. https://doi.org/10.3390/su11051277

Peng, Z., & Wan, Y. (2023). Generating business intelligence through automated textual analysis: measuring corporate image with online information. *Chinese Management Studies*, *17*(3), 545–572. https://doi.org/10.1108/cms-07-2021-0318

Provost, F., & Fawcett, T. (2013). Data Science and its Relationship to Big Data and Data-Driven Decision Making. *Big Data*, *1*(1), 51–59. https://doi.org/10.1089/big.2013.1508

Qiang, C. Z., Yamamichi, M., Hausman, V., Altman, D., & Unit, I. (2011). *Mobile Applications for the Health Sector_2011*. The World Bank.

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

Umadevi, M. (2020). Document comparison based on TF-IDF metric. *International Research Journal of Engineering and Technology*, *7*(2), 1546–1550.

Wan Min, W. N. S., & Zulkarnain, N. Z. (2020). Comparative Evaluation of Lexicons in Performing Sentiment Analysis. *Journal of Advanced Computing Technology and Application*, *2*(1), 1–8. https://jacta.utem.edu.my/jacta/article/view/5207

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

Weichbroth, P., & Baj-Rogowska, A. (2019). Do online reviews reveal mobile application usability and user experience? The case of WhatsApp. *Proceedings of the 2019 Federated Conference on Computer Science and Information Systems*, *18*, 747–754. https://doi.org/10.15439/2019f289

Zhou, H., & Slater, G. W. (2003). A metric to search for relevant words. *Physica A: Statistical Mechanics and Its Applications*, *329*(1–2), 309–327. https://doi.org/10.1016/s0378-4371(03)00625-3

This page intentionally left blank