

Article

A New Approach to Assess Sustainable Corporate Reputation with Citizen Comments Using Machine Learning and Natural Language Processing

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Abstract: This study investigates the assessment of sustainable corporate reputation through citizen comments and how it can be measured by sentiment analysis methods based on machine learning and text mining. The research analyses citizen feedback on municipalities in the field of public services and examines their impact on the social reputation of the services provided by municipalities. Support vector machines, one of the machine learning methods, was used for sentiment analysis. In the study, Google Maps comments of the citizens receiving services from the municipality were used. The results of the sentiment analysis reveal that sustainable corporate reputation is directly related to citizen satisfaction and feedback. In this context, municipalities should continuously receive feedback and make strategic improvements based on citizens' comments to ensure sustainable service quality. Municipalities are especially appreciated by citizens for their fast, effective, and high-quality services. However, some negative comments focus on issues such as the slowness of services, cleaning problems, and staff attitudes, indicating that certain improvements are needed. This feedback emphasises the need for continuous improvement in service quality.

Keywords: sustainable reputation; corporate; municipality; machine learning; sentiment analysis; text mining



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1. Introduction

Corporate reputation refers to the general perception and reputation of an organisation in the eyes of all stakeholders, and this perception is one of the most important factors that directly affect the long-term success of the organisation [1]. For a wide range of organisations, such as companies, non-governmental organisations, and public institutions, reputation management plays a vital role in providing competitive advantage, increasing customer loyalty, and gaining stakeholder trust. However, the sustainability of this reputation requires a broader approach beyond traditional strategic management processes. Especially for organisations providing public services, such as municipalities, corporate reputation has a critical importance in terms of ensuring social trust, increasing citizen satisfaction, and effective use of public resources [2].

The concept of sustainable corporate reputation is not only limited to building a good reputation in a certain period but also includes the processes of protecting and developing this reputation in the long term. In this context, sustainability principles are related to

fundamental elements such as social responsibility, environmental sensitivity, transparency, accountability, and continuous improvement [3]. The adaptation of organisations, especially those providing public services, to these elements makes it possible for them to sustain their reputation in the eyes of society [4]. A sustainable reputation requires organisations to continuously improve their service quality not only through positive feedback but also by analysing negative feedback and continuously improving their service quality in the light of this feedback [5,6].

Today, with the rapid advancement of technology and digitalisation, collecting and analysing citizen feedback has become more accessible than ever before. Comments on social media, mobile applications, and online platforms provide an important data source to reveal citizens' satisfaction and complaints about public services. At this point, artificial intelligence-based data analysis techniques such as text mining and sentiment analysis have become effective tools for extracting meaningful insights from large-scale data and measuring the sustainability of corporate reputation.

This study evaluates the corporate reputation of three large municipalities in Antalya province by analysing citizen comments on Google Maps [7]. The machine learning and text mining techniques used in the study aim to measure the impact of the services provided by municipalities on citizens and to reveal the role of these services on sustainable corporate reputation. The fact that the services are liked and appreciated by the citizens will positively affect the continuation of the good corporate reputation of the municipalities [8,9]. The sentiment analysis analyses how both positive and negative feedback are shaped and their impact on service quality, while also assessing the extent to which municipalities comply with sustainability principles in their interactions with citizens [10,11].

The originality of this study lies in its objective and data-driven assessment of sustainable corporate reputation through citizen feedback. While traditional reputation management studies usually rely on qualitative methods and surveys, this research draws meaningful conclusions from large-scale data sets using artificial intelligence-based text mining and sentiment analysis techniques. Citizen comments collected through a widely used platform such as Google Maps offer an innovative approach to measuring the social reflections of the services provided by municipalities. In addition, sentiment analyses obtained by using support vector machines (SVM), one of the machine learning algorithms in the study, provide a quantitative and comparative perspective when evaluating the sustainability of corporate reputation. In this way, a more in-depth and objective analysis of the service quality and reputation of municipalities is provided by going beyond the subjective and qualitative approaches frequently found in the literature.

As a result, this research provides important findings on how sustainable corporate reputation can be assessed based on citizen comments and provides strategic recommendations for municipalities to sustain their service quality. It is emphasised that corporate reputation should be shaped not only based on short-term achievements but also based on continuous feedback mechanisms and sensitivity to social expectations.

2. Literature

In recent years, with the digital transformation and the widespread use of social media, significant changes have occurred in the methods of measuring and evaluating corporate reputation. Traditional reputation measurement methods are being replaced by technological innovations such as big data analytics, machine learning, and sentiment analysis. In this context, measuring corporate reputation through digital data has become an increasing focus of scientific research. This review assesses the literature on the importance of machine learning and sentiment analysis in corporate reputation studies.

Machine learning is widely used to analyse large data sets, make predictions, and automate complex processes. Machine learning methods provide significant advantages, especially in measuring subjective and dynamic concepts such as corporate reputation. A study by Saura, Palos-Sanchez, and Cerdá Suárez (2019) used machine learning techniques to evaluate the reputation of brands by analysing comments on social media platforms [12].

This study analysed the impact of brands on online reviews using big data mining and deep learning algorithms. Similarly, Kim and Park (2020) determined the online reputation of companies with sentiment analysis and machine learning methods in their study and emphasised the predictive ability of these methods [13].

This study investigated how organisational reputation is managed in the Emfuleni Local Municipality in the Gauteng province of South Africa [14]. The study utilised a qualitative research approach and a case study design. Individual, in-depth, semi-structured interviews were conducted with eight participants until data saturation. Thematic analysis was used to analyse the data. The results show that reputation management is a multi-faceted concept that includes corporate social responsibility, emotional appeal, financial performance, products and services, vision and leadership, and the workplace environment. They also show that corporate communication is an important part of a local municipality as it serves to align the vision, culture, and image of the organisation.

Sayılganoğlu examined the activities carried out by the IBB public relations unit and analysed the effect of these activities on corporate reputation and the relationship between this effect and ethical rules [15]. In the study, semi-structured, in-depth interviews were conducted with 10 participants. According to the findings based on the analysis of qualitative data, the participant views are concentrated on the positive effect of compliance with the code of ethics on IBB's corporate reputation. In addition, compliance with social values and general moral principles also has an impact on corporate reputation. The results also indicate that unethical behaviour has a negative impact on corporate reputation.

Arslan and Karacaolu's aim is to reveal the effect of public officials' perceptions of corporate reputation on their service motivation [16]. The data for the study were collected from a total of 80 civil servants working in the district municipalities of Nevşehir province with the help of face-to-face survey techniques. According to the findings of the study, it was determined that public officials in municipalities perceive their organisations as reputable, and their service motivation levels are high. It was determined that there is a moderate and positive relationship between employees' perceptions of corporate reputation and service motivation.

Güllüpınar and Tekmen address the effect of the impressions left by the municipalities on the personnel, mayor, or services on the general perception of the municipality [17]. In this context, research on Giresun Municipality was conducted in the city centre. In the research, the image factors related to the representation power and services of Giresun Municipality based on the mayor and staff were determined, and the effect of these factors on the general perception of Giresun Municipality was examined. In the research, it was concluded that image factors are an important explanatory factor of the general perception of the municipality, and the biggest factor in the general perception is the mayor factor.

Yavuz and Zavalı, Ordu Metropolitan Municipality's posts on Twitter, an important social media platform today, between 1 September 2019 and 30 September 2019 were analysed using the content analysis method [18]. As a result of the study, it is understood that the relevant platform is actively used, as the posts made by Ordu Metropolitan Municipality on the Twitter platform between the mentioned dates are included in both national and local media organs. The posts were categorised as announcements, news, services, celebrations, promotions, and visits, and it was observed that most of the posts were made to inform the target audience. However, while some of the posts contribute to the corporate image of the municipality, it is thought that some of the posts harm the corporate image.

Pérez-Cornejo et al. examined city reputation and the role of sustainability in cities [19]. The results from Tobit analyses based on an international sample of 62 cities between 2015 and 2018 confirm that city sustainability is a determinant of city reputation. This study shows that the level of environmental, social, and economic sustainability positively affects city reputation. The results are of interest to local governments as they show the importance of efforts to increase the sustainability of the city to build a good city reputation.

Digital transformation and the proliferation of social media have led to major changes in corporate reputation measurement methods. Traditional methods are being replaced by innovative technologies such as big data analytics, machine learning, and sentiment analysis. Saura et al. [12] used machine learning to assess the reputation of brands through social media comments; similarly, Kim and Park analysed the reputation of companies with these methods, highlighting the high predictive power of machine learning. A case study conducted in Emfuleni Local Municipality revealed that reputation management is a multifaceted concept. Sayılanoğlu analysed the impact of IBB's public relations activities on corporate reputation and found that compliance with ethical rules had a positive effect. On the other hand, Arslan and Karacaoğlu found that public officials' perception of corporate reputation has a positive effect on their service motivation, while Güllüpınar and Tekmen found that leadership and staff image in municipalities shape the general perception of reputation. Yavuz and Zavalı [18] analysed that Twitter posts by Ordu Metropolitan Municipality affect corporate image; Pérez-Cornejo et al. revealed the determinant role of sustainability on reputation in cities.

The reviewed literature focusses on qualitative research methods, often using case studies and interviews, to explore corporate reputation management in municipalities. Key themes include the influence of corporate communication, ethical compliance, and image factors such as leadership and staff on reputation. Studies examined public officials' perceptions, the impact of social media content on corporate image, and the role of sustainability in shaping city reputation. These studies highlight the subjective perceptions of stakeholders and qualitative assessments of reputation.

The contribution of this study to the literature is that it provides a quantitative perspective by using machine learning-based sentiment analysis methods to measure the corporate reputation of municipalities. In the literature, it is seen that most of the studies on the reputation of municipalities are based on qualitative methods and are limited to methods such as interviews, case studies, or content analyses. These studies examine perceptions based on subjectivity when evaluating municipal reputation and focus on factors such as leadership, employee behaviour, and communication of local governments. However, machine learning algorithms such as support vector machines used in this study provide the advantage of objectively analysing citizen feedback in large-scale data sets.

The study analyses Google Maps comments on municipalities in Antalya and examines the citizen satisfaction levels of different municipalities with a comparative approach. Thus, it is shown that sustainable corporate reputation can be assessed not only perceptually but also quantitatively. This method objectively categorises positive, negative, and neutral statements in comments and provides data-based insights to identify the strengths and weaknesses of municipalities in service quality. The results of the study emphasise the importance of continuous feedback analysis in the sustainable reputation management strategies of municipalities and suggest that municipalities should make service improvements according to citizen satisfaction. In this respect, the study contributes to the literature on the social reputation of municipal services by providing a data-driven and objective perspective.

3. Materials and Methods

This study seeks an answer to the hypothesis that the emotional state expressed by citizens in their comments on municipal services directly affects the sustainable corporate reputation levels of municipalities. The proposed model consists of a three-stage process. In the first stage, the dataset is created, and text preprocessing is performed. In the second stage, the comments are classified according to their sentiment using support vector machines, one of the machine learning methods. In the third stage, the words in the comments are interpreted using text mining.

3.1. Data Set

The study comparatively analyses and interprets the corporate reputations of five local municipalities in Antalya by using sentiment analysis and text mining on the comments of citizens who receive services from these municipalities. Among the reasons for the selection of Antalya, being the 5th largest province of Turkey with a population of 2,696,249, its socio-economic status, intensive migration, and being a tourism city are important factors [18]. The data set was created by using the comments of citizens receiving services from the municipality on Google Maps. The reason for preferring Google Maps is that citizens can share their feelings and thoughts about the municipality freely and uncensored. Table 1 shows information of municipalities according to Google Maps.

Table 1. Information of municipalities according to Google Maps.

Municipality Name	Score	Number of Comments
M1	3.9	267
M2	3.9	612
M3	4.4	782

Table 2 shows examples of comments made on Antalya municipalities.

Table 2. Dataset example.

Municipality Name	Comments
M1	All staff in all departments are very, very interested. Citizens' problems are finalised in a very short time
	M1 provides quality service. All staff do their job professionally. It is an exemplary municipality.
M2	It is one of the few municipalities that provides modern and fair service to citizens.
	I call it friendly service and attention, Thank you
M3	I would like to thank everyone who works in a place that has an extremely interested staff and is extremely far from the atmosphere of the official office.
	We thank M3; the beach is clean, well-maintained landscaping is in place, and order are in place.

3.2. Text Mining

Text mining, an indispensable component of data analytics and artificial intelligence, involves the extraction of meaningful insights from extensive unstructured textual data. By leveraging sophisticated algorithms and methodologies derived from natural language processing (NLP), machine learning, and statistical analysis, text mining converts unstructured text into organised data, thereby unveiling concealed patterns, tendencies, and valuable insights [19]. This approach enables enterprises, scholars, and institutions to facilitate data-informed decision-making, discern customer sentiment, and identify emerging trends across diverse datasets spanning from social media content to scholarly publications.

Text mining is the systematic process of gleaning insights from textual data through the identification of prevalent patterns and trends, often accomplished via statistical pattern recognition methods [20]. This methodology typically encompasses the structuring of input text, derivation of a model from the restructured data, and ultimately, the assessment and comprehension of the generated output.

The primary objective of text mining encompasses the conversion of textual information into analysable data through the utilisation of natural language processing (NLP) and analytical methodologies. This entails the retrieval of information and data, lexical analysis for examining word frequency distributions, pattern recognition, tagging and annotation, information extraction, utilisation of data mining techniques, visualisation, and predictive analytics [21].

The fundamental elements of text mining comprise natural language processing (NLP), information extraction, text analysis, and data mining techniques. NLP techniques are

employed to comprehend the syntax, structure, and semantics of the text, enabling tasks such as sentiment analysis, entity recognition, and topic modelling [22]. Information extraction focuses on identifying specific data elements from the text, including names, dates, places, as well as more intricate patterns such as relationships and events. Text analysis involves scrutinising text to reveal patterns, trends, sentiments, and organising text into categories or themes. Data mining techniques encompass the application of algorithms to analyse structured data extracted from text to identify patterns or statistical relationships [23].

3.3. Machine Learning

Machine learning is a field of artificial intelligence that involves automating the processes of data-driven learning and decision-making for computers. This process enables algorithms to recognise patterns by analysing large data sets and make predictions based on these patterns [20,21]. The field of machine learning encompasses several distinct subcategories, including supervised learning, unsupervised learning, and reinforcement learning. Supervised learning involves training models using labelled data, whereas unsupervised learning involves working with unlabelled data to uncover latent structures within the dataset [22]. Reinforcement learning refers to the process of agents learning through reward or punishment mechanisms [23]. These methods are widely used in many fields today, especially in prediction, classification, and optimisation problems.

Support Vector Machines

Support vector machines (SVM) represent a robust machine learning algorithm employed for binary classification of datasets. SVM is known for its ability to solve linear and non-linear classification problems. Both types of classification offer various advantages for different data sets and problems.

Linear SVM is used when the data can be separated into two classes by a linear hyperplane. This means that the data can be divided into two classes on a plane. The aim of linear SVM is to find the hyperplane with the maximum margin between the two classes. This hyperplane is positioned to provide the largest distance between the data. The optimisation problem of linear SVM is as follows [24]:

$$\text{minimize } \frac{1}{2} \|w\|^2 \quad \text{subject to } y_i(w \cdot x_i + b) \geq 1, \dots, N \quad (1)$$

where w is the normal vector of the hyperplane, b is the bias term indicating the distance from the hyperplane. y_i is the class label of each data point (+1 or −1).

The success of linear SVM is quite high when the data are linearly separable. However, many real-world problems involve non-linear structures, so more complex methods may be required.

Non-linear SVM is used when the data are not separable in a linear way. In such data sets, the data often require a more complex structure rather than being linearly separated by a hyperplane. Non-linear SVM provides a solution for such cases by using ‘kernel’ functions. Kernel functions transform the data into a high-dimensional space, making it linearly separate. Some of the kernel functions are as follows [25]:

A polynomial kernel function transforms the data in a polynomial way.

$$K(x_i, x_j) = (x_i \cdot x_j + c)^d \quad (2)$$

The RBF (Radial Basis Function) kernel transforms the data with a Gaussian distribution and is defined by the formula:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (3)$$

These kernel functions can define nonlinear boundaries by transforming the data into a high-dimensional space. Thanks to this transformation, data points become linearly separable in high-dimensional space, and thus nonlinear problems are solved. Linear SVM is often used in text classification, spam filtering, and some biomedical data analyses. It provides a simple and effective classification [26]. Non-linear SVM is widely used in more complex data sets, for example in image recognition, natural language processing, and bioinformatics. Thanks to its kernel functions, it can model complex structures in data [27].

3.4. Sentiment Analysis

Sentiment analysis is a part of natural language processing that focuses on understanding the feelings and emotions expressed in a text. It is used to analyse the emotional tone of a text. It works by extracting subjective information to classify text emotions as positive, negative, or neutral. It looks at attitudes, opinions, and emotions communicated through text [28]. Sentiment analysis can show how people interact with certain topics and provide meaningful information to help businesses better understand public opinion.

When analysing a text, such as a customer review, tweet, or blog post, the sentiment is evaluated and labelled as positive, negative, or neutral. This classification is based on advanced analysis algorithms. Sentiment analysis involves a step-by-step process that starts with collecting data from sources such as reviews, social media, or surveys. Once the unstructured data is collected, it is preprocessed before being analysed using various techniques and algorithms, such as the sentiment analysis model [29]. Before using machine learning algorithms, text data must go through a preparatory stage called preprocessing. Sentiment analysis algorithms then analyse the text data by identifying patterns to classify and score sentiment. Rule-based algorithms use a word list or dictionary where each word is assigned a sentiment score. These algorithms use rules to classify sentiment without training a machine learning model. Automatic sentiment analysis uses machine learning algorithms (support vector machines, decision trees, and naive bayes) to automatically recognise sentiments in text data. Mixed approaches combine the unique strengths of different methods in combination to improve accuracy [30,31].

Sentiment analysis can be utilised by organisations to analyse direct communications, including conversations and interactions with customers through email, phone, WhatsApp, chatbots, and other channels. It is also valuable for analysing online communications such as customer comments on social media, blog posts, news articles, and online review sites [32].

3.5. Sustainable Corporate Reputation

Sustainable corporate reputation refers to the perceptions and opinions generally held by an organisation's stakeholders [4]. This perception includes the views of different stakeholder groups, such as customers, employees, investors, and society, about the firm and is referred to as corporate reputation. Sustainable corporate reputation encompasses various elements such as a firm's ethical values, financial performance, product and service quality, customer service, and general business behaviour.

An organisation's sustainable corporate reputation has a major impact on its long-term success. The perception of the organisation in the eyes of its stakeholders makes it a valuable intangible resource [33,34]. A sustainable corporate reputation is directly related to customer trust. Customers are more likely to interact with and support firms that have a solid reputation, are reliable, observe ethical values, and offer quality products and services. In this case, customer behaviour is greatly influenced by the reputation of the firm, which directly affects brand preferences and purchasing decisions [35,36].

A sustainable reputation also plays a critical role in attracting and retaining talented employees [37]. Talented individuals want to work for companies that are not only profit-orientated but also ethical and socially responsible. Having a strong corporate reputation increases the capacity to attract and retain qualified employees. A company with a good

reputation creates pride and motivation in its employees, which directly affects productivity and overall organisational performance positively.

A sustainable reputation in the business world is also of great importance in relations with investors. Investors and other financial stakeholders conduct in-depth analyses when assessing a company's reputation [38]. A strong corporate reputation is an important factor in attracting investment and having a positive impact on share prices. On the other hand, a poor reputation can alienate potential investors and lead to financial losses and a decline in market capitalisation. Therefore, careful management and continuous improvement of reputation are essential for a company to maintain its financial position in today's challenging economic environment.

Sustainable corporate reputation is a reputation dimension which is shaped based on environmental, social, and governance (ESG) criteria. ESG elements express companies' responsibility towards the environment, social impact, and transparency and accountability of governance policies and constitute the basic components of a sustainable corporate reputation [39]. In this context, the ESG performance of companies strengthens the long-term reputation of the organisation by reducing the use of natural resources, making social contributions, and increasing stakeholder trust through ethical management practices. In addition, ESG criteria create a favourable perception among investors and customers and reveal that the financial success of companies that develop sustainable business strategies can also increase [40]. Therefore, strong ESG adoption is seen as a critical tool to ensure the sustainability of corporate reputation.

4. Results and Discussion

A Python program was used to analyse the comments of central municipalities obtained from Google Maps. In this study, machine learning methods are utilised to perform sentiment analysis. User comments were processed with the support vector machines (SVM) algorithm and categorised according to positive, negative, and neutral moods. With this approach, emotional tendencies in texts were systematically analysed, and comments were categorised into mood categories.

In the first stage of the study, the text data must go through a preparatory stage called preprocessing. This step is very important for sentiment analysis because it transforms the raw text into a structured form that machine learning algorithms can easily understand. Tokenization breaks the text into smaller units (like chopping vegetables) for better understanding. Stop word removal gets rid of common, unimportant words to simplify the data. Stemming reduces words to their basic form to ensure accuracy [41].

The data set is divided into training and test sets. While the parameters of the models are determined in the training process, the performance of the models is evaluated in the testing process. Although there is no specific rule for dividing the data set into training and test sets, the most appropriate ratio is usually determined using the trial-and-error method. In this study, tests were performed on various ratios (60–40%, 70–30%, 80–20%, etc.), and the most successful result was obtained with an 80% training and 20% testing ratio.

4.1. Sentiment Analysis with Machine Learning

In this study, Support Vector Machines (SVM), one of the machine learning methods, was used to classify comments according to their sentiment. This method is preferred for accurately and effectively categorising text data into different sentiment categories.

The metrics used to evaluate the accuracy and efficiency of the model's predictions are of great importance. In this context, metrics such as precision, recall, accuracy, and F1 score are widely preferred to measure classification performance. Each metric assesses different characteristics of the model and may have varying priorities in different application scenarios.

Precision is a metric that determines the ratio of positive samples correctly classified by a model to all samples predicted as positive by the model. This metric is particularly important in scenarios where the cost of false positives is high. Precision is calculated as the

ratio of the number of true positive predictions, called True Positives (TP), to the number of false positive predictions, called False Positives (FP).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (4)$$

Recall is another important metric that measures how many true positive samples the model can accurately predict. This metric is especially critical when the cost of false negatives is high. Sensitivity reflects the relationship between the number of true positive predictions (TP) and the number of false negative predictions (FN).

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (5)$$

Accuracy is another common metric that measures the proportion of all instances correctly predicted by the model out of the total predicted instances. This metric is used to assess the overall performance of the model but can give misleading results in imbalanced data sets. Accuracy is the ratio between true positives (TP) and true negatives (TN) and false positives (FP) and false negatives (FN).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (6)$$

The F-measure or F1 score is defined as the harmonic mean of precision and sensitivity and aims to balance these two metrics. The F1 score is used to evaluate model performance more comprehensively, especially in classification problems where both precision and sensitivity are important.

$$\text{F1} = \frac{2 * \text{Recall} * \text{Precision}}{\text{Precision} + \text{Recall}} \quad (7)$$

These metrics are used to comprehensively evaluate the performance of classification models, and each is important in different circumstances. Precision, sensitivity and F1 score generally provide more meaningful results on imbalanced data sets, while the accuracy metric measures the overall predictive success of the model. Table 3 shows performance measurement results of model.

Table 3. Performance measurement results.

Municipality Name	Precision	Recall	Accuracy	F Score (F1)
M1	0.947	0.922	0.905	0.934
M2	0.964	0.937	0.923	0.950
M3	0.959	0.881	0.875	0.918

When the results of sentiment analysis with support vector classification (SVC) are analysed, the performance metrics obtained for M1, M2, and M3 Municipalities are remarkable. M1 performed very effectively in identifying positive comments with 94.7% precision, 92.2% sensitivity, 90.5% accuracy, and a 93.4% F1 score. M2 Municipality had the highest precision (96.4%) and sensitivity (93.7%) values, with an overall accuracy of 92.3% and an F1 score of 95.0%. M3 Municipality, with 95.9% precision, 88.1% sensitivity, 87.5% accuracy, and a 91.8% F1 score, showed a slightly lower but still successful performance compared to other municipalities. These results show that M2 Municipality is the most successful municipality in sentiment analysis based on comments.

Figure 1 shows that M2 Municipality outperformed the other two municipalities in all metrics, especially in terms of precision and sensitivity. M1 also performed well in general, while M3 Municipality underperformed compared to the other two municipalities. This confirms that M2 Municipality is the most successful municipality in sentiment analysis based on comments.

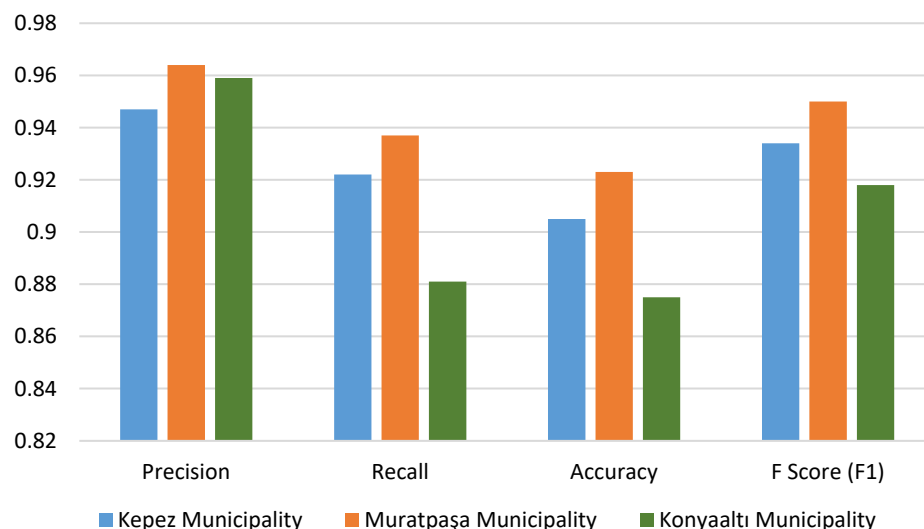


Figure 1. Comparison of model results.

As a result of text preprocessing, 76 comments for M1, 293 comments for M2 Municipality and 280 comments for M3 Municipality remained. Table 4 shows the sentiment analysis of these comments.

Table 4. Sentiment analysis of municipality comments.

Municipality Name	Positive	Neutral	Negative
M1 Municipality	76	18	18
M2 Municipality	199	56	38
M3 Municipality	193	51	36

Table 4 shows M1 Municipality's positive comment rate is quite high at 67.86%, indicating that the municipality is generally evaluated positively. Neutral and negative comment rates are equal at 16.07%, indicating that there are deficiencies or dissatisfaction with some services. The positive comment rate of M2 Municipality is very close to M1 Municipality with 67.92%, which shows that overall satisfaction is high. The neutral comment rate is 19.11%, slightly higher than that of M1 Municipality. The rate of negative comments is lower, at 12.97%, indicating that dissatisfaction is relatively lower. M3 Municipality has the highest positive comment rate with 68.93%, indicating that this municipality received more positive evaluations than the other two municipalities. The neutral comment rate is 18.21%, close to M2 Municipality. The rate of negative comments is the lowest, at 12.86%, indicating that this municipality has the least dissatisfaction. Figure 1 shows the sentiment analysis comparison for the central municipalities in Antalya.

Figure 2 shows all three municipalities have high positive comment rates, but M3 Municipality stands out as the municipality most positively evaluated by citizens, as it has both the highest positive comment rate and the lowest negative comment rate. M1 and M2 municipalities also received generally good evaluations, but the negative and neutral comment rates for these municipalities are slightly higher than for M3 Municipality. This may indicate that these municipalities need to make improvements in some service areas.

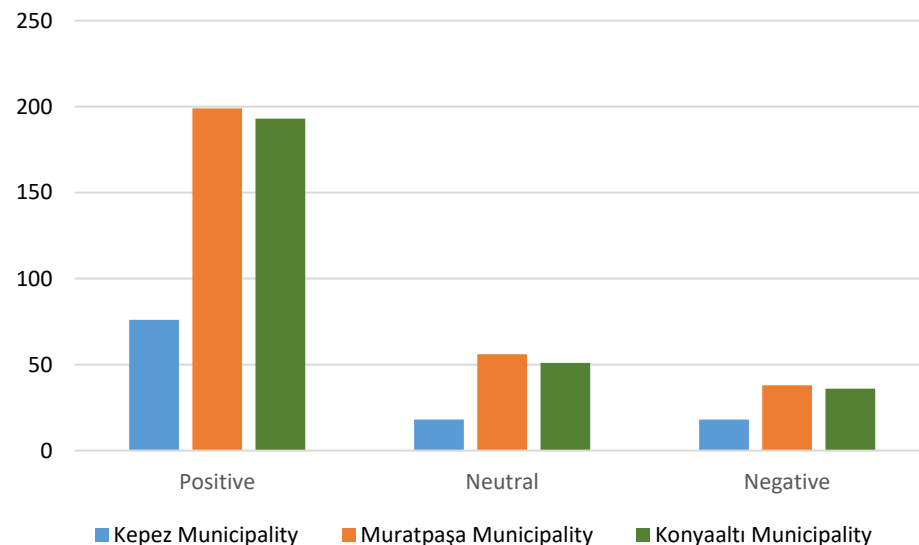


Figure 2. Comparison of municipalities' sentiment analysis.

4.2. Text Mining Analyses

In the text mining analysis, the word frequency analysis method was applied to determine the frequency of use of words in the text; thus, important keywords and themes were identified. In addition, word cloud analysis was performed to visually represent the most frequently used terms and to develop an intuitive understanding of the density of these terms in the text. These analyses were used to understand the overall structure of the data and to reveal meaningful patterns in the text.

4.2.1. Word Frequency Analysis

The most common text mining approach is n-gram, which implements bag-of-words. An n-gram is a contiguous sequence of words in a text. N-grams are a powerful tool used to extract meaningful information from large text datasets. They are used in various applications, such as text classification, topic modelling, and sentiment analysis. N-grams are classified according to the number of words, syllables, or characters present in a text. For example, a bigram consists of two words, and a trigram consists of three words [42].

Word frequency was created from the comments made for each municipality. In text mining, word frequency is a technique that involves counting the number of times each word occurs in each text collection (such as documents, articles, or web pages). It helps to identify the most frequent words and their frequency.

The comments from citizens regarding M1 Municipality's services, as outlined in Table 5, provide key insights into the municipality's sustainable corporate reputation. Positive words such as "positive", "successful", "good", and "helpful" reflect the overall satisfaction of citizens with the quality of services and the performance of municipal employees, reinforcing the municipality's strong reputation. The appreciation of services, particularly in areas like cleanliness and landscaping, underscores the positive impact of the municipality's operations. However, negative feedback, including terms like "indifferent", "victimization", and "criticisms" related to "transportation", and "roads", points to gaps in service delivery, particularly in infrastructure and responsiveness to citizen needs, which, if unaddressed, could harm the municipality's long-term reputation. Neutral terms such as "nice" and "polite" provide balanced observations, describing the current service environment and employee conduct without strong emotional connotations. To ensure a sustainable corporate reputation, M1 Municipality must build on the positive feedback by maintaining service quality and addressing the negative issues raised, particularly in responsiveness and infrastructure improvement. By doing so, it can foster long-term trust and satisfaction among citizens, which is essential for sustaining a positive public image over time.

Table 5. Word frequency list of M1.

Positive	Neutral	Negative
Successful	Indifferent	Beautiful
Good	Victimization	Clean
Helpful	Transportation	Indifferent
Service	Roads	Polite
Clean	Bad	Hardworking

The feedback from citizens regarding M2 Municipality's services, as reflected in Table 6, provides important insights into the municipality's sustainable corporate reputation. Positive comments, such as "wonderful", "beautiful", and "excellent", emphasise the high quality of services and the overall satisfaction of citizens, reinforcing the municipality's ability to meet expectations and contribute to a strong and sustainable reputation. The term "successful" highlights the municipality's achievements in its projects, further strengthening its corporate image. However, negative feedback, including words like "crowded", "car park", and "filth", points to issues in service efficiency, parking, cleanliness, and public transportation, indicating areas where improvement is necessary to avoid damaging its reputation. These concerns, along with the recurring mention of "waiting" times, suggest that service delays are a key area for enhancement. Neutral comments provide a balanced perspective, with terms like "can be improved" and "peaceful" offering insights into both areas for development and positive outcomes such as a calm environment. By addressing these areas and continuously improving service quality, M2 Municipality can maintain and enhance its sustainable corporate reputation. Focusing on reducing negative feedback, particularly regarding operational inefficiencies, while leveraging positive experiences, will ensure long-term citizen satisfaction and trust, which are essential for the sustainability of the municipality's reputation.

Table 6. Word frequency list of M2 municipality.

Positive	Neutral	Negative
Great	Crowd	Evolve
Beautiful	Park	Peaceful
Perfect	Bus	Staff
Service	Waiting	Waiting
Successful	Transport	Satisfied

The citizen feedback on M3 Municipality's services, as seen in Table 7, provides valuable insights into its sustainable corporate reputation. Positive comments such as "successful", "great", and "landscape" highlight the municipality's strong performance in meeting expectations, preserving natural beauty, and delivering satisfactory services, all of which are essential for building and maintaining a sustainable reputation. However, negative comments like "waiting", "environment", and "employees" indicate that improvements are needed in service efficiency, environmental management, and staff performance to prevent damage to its corporate image. Issues such as stray animal management, as reflected in the word "dogs", and overall "performance" concerns further suggest areas requiring attention to ensure long-term satisfaction. Neutral comments provide an objective view of the municipality's current services, including communication infrastructure ("telephones"), transportation ("roads"), and tax policies, offering an informational snapshot without clear emotional implications. To strengthen its sustainable corporate reputation, M3 Municipality must leverage the positive feedback while addressing service delays, environmental concerns, and other deficiencies highlighted in the negative comments. By continuously improving these aspects, the municipality can maintain citizen trust and satisfaction, key elements of long-term reputation management.

Table 7. Word frequency list of M3 municipality.

Positive	Neutral	Negative
Successful	Waiting	Phones
Great	Environment	Roads
Landscape	Employees	Service
Service	Dogs	Tax
Location	Performance	Animals

4.2.2. Word Cloud Analysis

This makes it easier to understand your data and make inferences from it. Seaborn is a data visualisation library built on the Matplotlib library in Python. Seaborn is widely used for data analysis and visualisation in various industries. In this study, a word cloud was created using the Seaborn library. A word cloud is a visual representation of the words in a text, sized according to their frequency of use. The more frequently words are used, the larger they appear in the word cloud

Figure 3 shows the word cloud of M1 municipality comments. The word cloud generated from citizen comments about M1 Municipality provides significant insights into the municipality's sustainable corporate reputation. Frequently used terms such as "municipality", "service", "work", and "staff" highlight the focus areas of citizen feedback. The prevalence of positive expressions like "help", "very", "good", "thank", and "nice" indicates that the municipality is generally perceived favourably. However, words such as "problem", "slowness", "cleanliness", and "parking" emphasise various areas that require improvement, ranging from service speed to infrastructure. By actively addressing these concerns and continuously enhancing service quality, the municipality can increase citizen satisfaction and strengthen its long-term reputation.

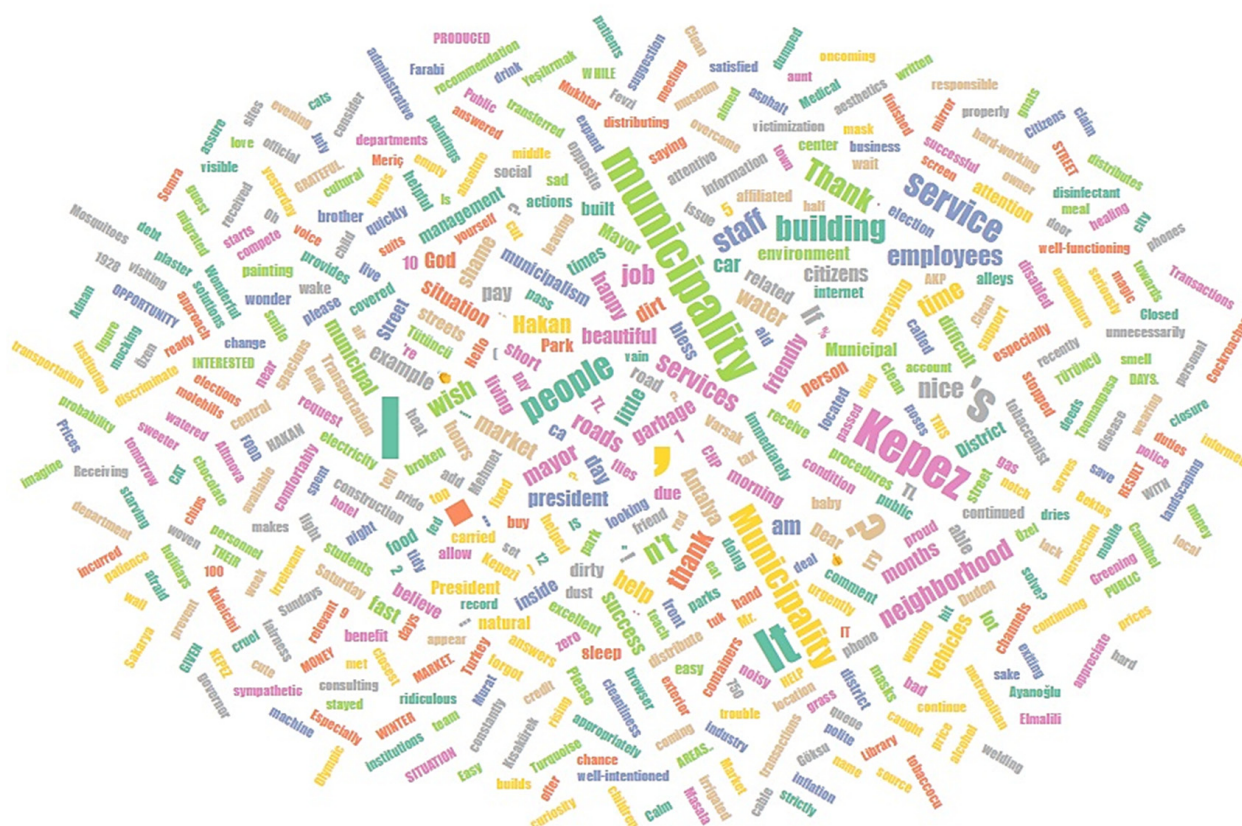


Figure 3. Word cloud of M1 Municipality comments.

Figure 4 shows the word cloud of M2 municipality comments. This word cloud, created from citizen comments about the M2 municipality, provides valuable insights into the public perception of the municipality's corporate reputation. Frequently used words like "municipality", "thank", and "work" indicate a generally positive view of the municipality's actions and services. The presence of terms such as "thank", and "service" suggests that citizens appreciate the services provided by the municipality and express gratitude in their interactions. Furthermore, the repeated appearance of words like "municipality" and "work" emphasises the municipality's active role and responsibilities. From a sustainable corporate reputation perspective, this word cloud reflects a strong, positive image of the municipality as a reliable, service-oriented, and active entity in the eyes of the public. It suggests that the municipality's reputation management strategies are yielding positive results.



Figure 4. Word cloud of M2 Municipality comments.

Figure 5 shows word cloud of M3 municipality comments. This word cloud, generated from citizen comments about the M3 municipality, is a valuable tool for assessing how the municipality is perceived in terms of public relations and sustainable corporate reputation. Prominent words like “municipality”, “thank”, “work”, “service”, and “staff” suggest a high level of citizen satisfaction with the services provided. The frequent occurrence of words such as “thank”, “service”, and “staff” indicates that the municipality’s personnel receive positive feedback, and the services are appreciated by the public. Additionally, the presence of terms like “place”, “friendly”, “good”, and “helpful” reflects a positive perception of both the physical and human aspects of the municipality’s services. From the perspective of sustainable corporate reputation, this data demonstrates that the M3 municipality has established a strong, positive relationship with its citizens, with services that are well-regarded and an overall favourable public image.



Figure 5. Word cloud of M3 Municipality comments.

In order to better understand the practical implications of the results of this study for municipal management, it is important to identify service areas that need to be improved in line with the data obtained from citizen feedback. We will focus on how negative feedback on specific areas such as cleanliness, staff attitude, service speed, and car parking can be used to ensure the sustainability of municipal service quality.

This study evaluated the sustainable corporate reputation of M1, M2, and M3 based on citizen comments and showed that the overall satisfaction levels are high. In particular, the fact that M3 Municipality has the highest rate of positive comments reveals that the municipality has created a sustainable corporate reputation by meeting citizen expectations to a great extent. In the literature, it is stated that corporate reputation directly affects factors such as economic growth, citizen satisfaction, and public trust [43]. In this context, fast, effective, and high-quality services provided by municipalities play a critical role in ensuring these three basic elements.

The results of the sentiment analysis show that although overall satisfaction is high, municipalities need improvement in some areas. Negative comments particularly highlight problems related to transport, cleanliness, and staff attitudes. These findings are in line with the crisis management theory emphasised by Coombs (2007) and suggest that municipalities should focus on continuous improvement processes by taking negative feedback into account [44].

The use of machine learning-based sentiment analysis in this study allowed for an objective and rapid analysis of large data sets and overcame the limitations of traditional qualitative methods. Liu (2012) also stated that sentiment analysis is a critical tool in corporate reputation management and emphasised the applicability of such technologies in different sectors [45]. Therefore, the methods used in this study can be applied not only for

municipalities but also for other public and private sector organisations and offer a wide range of applications for future research.

5. Conclusions

This study emphasises the importance of citizen feedback in the management of sustainable corporate reputation. The impact of the services provided by municipalities on citizens is one of the key elements of building a sustainable reputation. The results show that positive comments have positive effects on the reputation of municipalities, while negative feedback provides important clues for the sustainability of service quality. From a sustainability perspective, municipalities should take steps to improve service quality and strengthen their corporate reputation by continuously analysing citizen feedback.

The corporate reputation of municipalities significantly influences economic growth, resident satisfaction, public trust, and overall community well-being. Reputation plays a vital role in economic growth, effective governance, and community well-being and is a key factor in the overall success and resilience of municipalities.

Machine learning-based sentiment analysis plays an important role in measuring corporate reputation by providing an objective assessment of emotions and attitudes on large data sets. The application of this method overcomes the limitations of traditional qualitative methods, allowing for the automatic analysis of comments from a wider and more diverse range of data sources. Algorithms such as support vector machines provide data-driven insights to decision makers by identifying and classifying hidden sentiment patterns in large-scale data. The fact that this analysis method can be applied to different sectors, institutions, and brands other than municipalities shows that machine learning-based sentiment analysis has a wide range of applications.

According to the sentiment analysis, Kepez, Muratpaşa, and Konyaaltı Municipalities have gained the satisfaction of citizens with a high rate of positive comments in general. Konyaaltı Municipality has the highest rate of positive comments with 68.93 percent, while the rate of negative comments is the lowest with 12.86 percent, indicating that there is the least dissatisfaction. Although Muratpaşa Municipality has the highest rate of neutral comments with 19.11%, the rate of negative comments is still low with 12.97%, indicating that the overall satisfaction is high.

The word cloud analysis reveals that the services provided by Kepez, Muratpaşa, and Konyaaltı Municipalities generally receive high satisfaction ratings. Citizens particularly value the speed, quality, and aesthetics of the services. Positive feedback highlights the helpfulness of municipal staff and the overall service quality. On the other hand, negative comments mainly focus on issues such as service delays, cleanliness problems, staff behaviour, and parking challenges. Neutral comments provide insights into the general state of services, timing, and staff performance. These responses indicate that while the municipalities are generally well-regarded, there are areas that require improvement.

All three municipalities demonstrate high levels of satisfaction and maintain a positive corporate reputation. Citizens' positive feedback underscores the effectiveness and adequacy of the services provided. However, it is crucial for municipalities to continuously enhance service quality, particularly in response to negative feedback. Key areas for improvement include addressing service gaps, implementing more efficient solutions for transportation and cleanliness, and enhancing staff training and engagement. Furthermore, analysing neutral comments can offer valuable information about the overall condition of services, helping to inform and guide ongoing improvement efforts.

By analysing feedback from online platforms at regular intervals, managers can identify levels of satisfaction with services and areas for improvement. Such mechanisms will contribute to the sustainable reputation of municipalities while ensuring a quick response to citizens' demands. Furthermore, digital solutions such as user-friendly mobile applications and interactive feedback tools can be developed to better monitor service performance. These approaches will increase the capacity of municipalities to provide citizen-orientated services and provide significant support to continuous improvement processes.

This study has some limitations. As the analysis relies heavily on comments from platforms such as Google Maps, it could be triangulated with a larger data set or feedback from different platforms. Comments on such platforms are usually from a specific time period, which could be extended in future studies to examine longer-term trends. Furthermore, while the machine learning algorithms used successfully reveal general trends in large datasets, they may not fully capture some more subtle emotional expressions or complex language features. Nevertheless, the methods presented in this study provide valuable contributions to decision support processes for municipalities and shed light on sustainable reputation management strategies.

Future research could be extended to include different data sources and demographic characteristics, enabling municipalities to assess citizen satisfaction more comprehensively. Firstly, analysing the reputations of municipalities in different cities, as well as private sector organisations or other state institutions providing public services, with similar methods would increase the generalisability of the study. Furthermore, the inclusion of a wider range of data, such as social media, mobile applications, and news websites, in addition to data obtained from platforms such as Google Maps, would allow for a more comprehensive analysis of citizen feedback. The development of machine learning algorithms and the use of deep learning techniques can enable more complex sentiment and issue analyses. Finally, future research could also examine how different cultural and demographic variables play a role in the measurement of sustainable corporate reputation, contributing to the alignment of reputation management strategies with regional and cultural awareness.

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