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RESEARCH ARTICLE

A Proposed Service Quality Measurement Model using Sentiment Analysis and Text Mining: The Case of Water and Sewerage Services

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Abstract

This study proposes a new model for service quality measurement using sentiment analysis and text mining techniques. This model aims to overcome traditional methods' time, cost and implementation difficulties and provide a more dynamic and efficient approach to service quality measurement. In addition, in this model, instead of the dimensions used in service quality measurements, such as SERVQUAL or SERVPERF, it is shown how to determine new categories and keywords specific to the service sector in which the model is used by text mining. Thus, it is aimed at something other than reaching more accurate results in service quality measurement. To achieve the model's purpose, it aims to develop a service quality measurement model using social media data processed by text mining and sentiment analysis. To find an answer to this question, the keywords "flood", "meter", "rain", "irrigation", "infrastructure", "sewerage", "sewage", "maintenance hole ", "aski", "waterless", "water" were extracted from 109.844 tweets sent to the Twitter account of a municipality between 2016 and 2022 by text mining method. Service quality was measured by subjecting 5766 tweets containing the keywords extracted to sentiment analysis. As a result of the service quality measurement, 1922 negative, 973 positive and 2871 neutral tweets were identified. The average negative score was 0.51, the average positive score was 0.11, and the average neutral score was 0.38.

Keywords: *Sentiment Analysis, Text Mining, Service Quality, Twitter Data Analysis*

Öz

Bu çalışmada, duygu analizi ve metin madenciliği teknikleri kullanılarak hizmet kalitesi ölçümü için yeni bir model önerilmiştir. Bu model, geleneksel yöntemlerin karşılaştığı zaman, maliyet ve uygulama güçlüğünün üstesinden gelmeyi ve hizmet kalitesi ölçümüne daha dinamik ve verimli bir yaklaşım sağlamayı amaçlamıştır. Ayrıca bu modelde SERVQUAL veya SERVPERF gibi hizmet kalitesi ölçümünde kullanılan boyutların yerine metin madenciliği ile modelin kullanıldığı hizmet sektörüne özel yeni kategoriler ve anahtar kelimelerin nasıl belirleneceği gösterilmiştir. Böylelikle hizmet kalitesi ölçümünde daha doğru sonuçlara ulaşılması hedeflenmemiştir. Çalışmada önerilen modelin amacına ulaşabilmesi için metin madenciliği ve duygu analiziyle işlenen sosyal medya verilerinden hizmet kalitesi ölçüm modelinin nasıl geliştirileceği sorusuna yanıt aranmıştır. Bu soruya yanıt bulabilmek için bir belediyenin Twitter hesabına 2016-2022 yılları arasında gönderilen 109.844 tweet'den metin madenciliği yöntemi ile belediyenin vermiş olduğu su ve kanalizasyon hizmetleriyle ilgili olarak "sel", "sayaç", "yağmur", "sulama", "altyapı", "kanalizasyon", "lağım", "rögar", "aski", "susuz", "suya" anahtar kelimeleri çıkartılmıştır. Çıkartılan anahtar kelimelerin geçtiği 5766 tweet duygu analizine tabi tutularak hizmet kalitesi ölçümü gerçekleştirilmiştir. Yapılan hizmet kalitesi ölçüm neticesinde 1922 olumsuz, 973 olumlu ve 2871 nötr tweet tespit edilmiştir. Ortalama olumsuz puan 0,51, ortalama olumlu puan 0,11 ve ortalama nötr puan 0,38 olarak hesaplanmıştır.

Anahtar Kelimeler: *Duygu Analizi, Metin Madenciliği, Hizmet Kalitesi, Twitter Veri Analizi*

Introduction

Social media, which emerged with the introduction and development of the Internet, has affected human life in all areas. New phenomena in human life have changed the behaviour of all organisations and institutions. Just as human life is affected by social media, the institutions and organisations created by people have been and continue to be affected by this digital revolution. Organisations that cannot keep up with the transformation that occurs due to emerging paradigms or that keep up incorrectly cannot fulfil their functions and fail. The model proposed by the researchers is a new proposal for organisations to keep pace with digital change.

With the development and spread of technology, people's accessibility to technology and the time spent with technology have increased. Internet traffic grew 30 times between 2000 and 2014, connecting four out of ten people worldwide (Kotler et al., 2017). By 2022, it is reported that nearly five billion people will have an internet connection, and more than four billion people will use social media (Kemp, 2022). Considering the rapid increase in usage rates over the years and today's usage rates, the communication paradigms of people with each other and with organisations have changed. With advances in communication technology and better access to social networks, people are more likely to express their opinions and feelings with their friends on social media platforms. Users can communicate their positive or negative views about the products and services they purchase or use daily to their followers, friends, and direct contacts through Twitter, a social media platform. With this radical change in communication paradigms, widely used social networking sites such as Twitter have started to be used as business tools. (Levy & Birkner, 2011).

Analysing websites containing large amounts of data in terms of content and usage is essential for both users and organisations. They are analysing the content created by users on the Internet interests many sectors, such as politicians, companies, public institutions, and organisations. For these reasons, the analysis of data created on the internet has attracted the attention of researchers (Aydogan & Ali Akcayol, 2016). Organisations maintain and improve their service quality by considering user reviews and complaints. Since complaints from users are written in natural language expressions, especially in social media, there are difficulties in extracting and processing meaning from these messages (Islami et al., 2021). Researchers use sentiment analysis techniques to process social media data to overcome these challenges.

Sentiment analysis analyses people's opinions, emotions, evaluations, appraisals, valuations, attitudes, and feelings about products, services, companies, individuals, tasks, events, topics, and their characteristics (Alnawas & Arıcı, 2018). Sentiment analysis is used in many political, social, science, and technology disciplines, including public health, history, art, and economics. Companies use sentiment analysis to measure the reputation of their brands and understand their customers (Andrea et al., 2015). Similarly, product managers use sentiment analysis to improve user experiences and satisfaction scores and examine product and service quality (Fang & Zhan, 2015).

Text mining techniques are also used to process social media data. Text mining is a sub-branch of data mining, defined as accessing previously unknown information by computer by processing documents written on the subject (Akyüz & Gülten, 2022). Text mining is a study carried out using data on the internet network (Artsin, 2020).

Texts constitute the data source in text mining. First, a source selection suitable for the purpose should be made, and ineffective words should be separated from the texts and made suitable for processing. After this process, text data are statistically evaluated at the presentation stage and subjected to weighting processes called term frequency and reverse document frequency. Finally, new information discovery is made using classification, clustering, and sentiment analysis (Beşkirli et al., 2021).

The success of services is checked by measuring them with service quality measurement tools. Most existing research on service quality uses traditional survey-based techniques such as AHP, SERVQUAL, or SERVPERF. These survey-based approaches have limitations due to a lack of temporal analysis and limitations in respondents' recall of past events. As customers' use of social media becomes more widespread, more consumers share their shopping or service experiences on social media using websites, blogs, Facebook, and Twitter (He et al., 2018).

This study proposes a new service quality measurement model using sentiment analysis and text mining. In order to present this new model, the official account of a municipality was labelled, and 109.844 tweets created by users between 2016 and 2022 were subjected to text mining. As a result of text mining, 5766 tweets were identified as related to the municipality's water and sewerage services. The related tweets were scored with the sentiment analysis method on the Microsoft Azure Cognitive Services platform to measure the quality of the service. It has been observed that the success of Azure language services in negative comments is better than IBM Watson NLU and Google Cloud (Ermakova et al., 2021).

Related Works

With the increasing use of social media and the rapid processing of social media data, sentiment analysis has become essential for analysing users' thoughts. With the sentiment analysis technique, businesses aim to measure the quality of their service to their customers faster. For this reason, it was tried to determine the airport service quality by analysing the data of London Heathrow Airport's Twitter account with the sentiment analysis method. As a result of their analysis using 4392 tweets, the researchers identified 23 characteristics that can be compared with airport service quality scales. They stated that their findings have features that can improve airport service quality and carry new insights that can be implemented for airport management (Martin-Domingo et al., 2019).

Stating that the content created by online users on social media websites for reasons such as consumer experience, user feedback, and product review is the primary data source for both consumers and businesses, the researchers analysed 70.103 opinions with sentiment analysis method to measure hotel service quality based on the SERVPERF model. According to the findings, they categorised opinions according to the SERVPERF model's five dimensions: physical assets, reliability, enthusiasm, assurance, and empathy. They scored them with sentiment analysis (Duan et al., 2016).

Twitter data of three sizeable retail pharmacy organisations in the United Kingdom were collected, and sentiment analysis was conducted to determine the social media usage of pharmacies and the most discussed topics by consumers and to contribute to business intelligence by identifying the key points that need to be improved as a result of sentiment analysis. The study processed the data collected with application interfaces with text mining, sentiment analysis, and data mining methods. After processing the data, product, marketing, technology, pharmacy, customer relations, drug treatment, waiting time, store operation, shopping, and additional service topics and the elements related to these topics were revealed. Tweets collected according to the identified topics were subjected to sentiment analysis, and three different pharmacy retailers were compared with each other (Zhan et al., 2021).

Suggesting that despite the increasing opportunities for managers to use social media in their decision-making processes, social media has not been examined much with sentiment analysis for public services due to the large volume and noisy nature of big data; the researchers used a Python program to collect tweets about the UK National Health System and classified them according to SERVQUAL dimensions to monitor perceived service quality. This method identified keywords for SERVQUAL service quality dimensions by measuring public perceptions of NHS healthcare quality. The researchers found similar results by comparing the sentiment analysis measurement with the traditional service quality measurement survey method. They concluded that this method is a complementary tool for more expensive national-scale surveys and is valuable as a new method combining text mining with SERVQUAL (Lee et al., 2021).

Twitter data of two large companies operating in the US retail sector were analysed, classified according to service quality components, and subjected to sentiment analysis. In this way, the process of collecting social media data, turning it into big data, and processing it into helpful information for businesses has been revealed. A better understanding of customers was provided by evaluating the information obtained regarding service quality. Researchers who argue that the perception of service quality revealed by data collected with traditional data collection methods such as surveys and focus groups is static due to the time-consuming and more difficult data collection methods argue that data can be collected more dynamically and quickly through social media and can be processed effectively with text mining and sentiment analysis (He et al., 2018).

In China, which has had the largest share in the automobile market since 2009, a proposal is presented to create a competitive advantage by developing quality management and marketing strategy by analysing customer opinions through sentiment analysis and classification. Researchers suggest that analysing user-generated content with sentiment analysis better reflects customer opinions than traditional product performance analysis based on manufacturers' internal data and expert opinions (Liu et al., 2019).

Researchers point out that social media data is very diverse, and different data is obtained from different sources, which is often overlooked. Therefore, they propose a framework that dynamically processes and analyses social media data according to its characteristics. This framework includes collecting data from social media, cleaning noise data, sentiment analysis, opinion analysis, and text analysis and presenting it to the user (Ali et al., 2022).

Researchers who analysed the data about the Hilton hotel through the Trip Advisor application, where hotels can be rated to reveal customers' opinions about hotels and to create insights for businesses and help decision-making, stated that users use negative words such as "rude", "terrible", "broken", "dirty" to express their dissatisfaction. By using these words, they analysed the comments on a word-based basis. (Chang et al., 2019).

Researchers collect relevant user comments from various social media platforms through different programs and plugins when the studies are examined. The collected comments are processed with sentiment analysis techniques and text mining to extract meaningful data. Using these techniques, researchers can quickly analyze users' opinions and their opinions about the area where they receive service. The analyses provide recommendations for service quality measurement.

In some studies on service quality measurement, the data collected were analysed according to the dimensions of classical scales such as SERVQUAL and SERVPERF used in service quality measurement. In some studies, researchers analysed emotions according to the words they determined according to the dimensions of service quality measurement.

Sentiment Analysis and Its Use with Twitter

Sentiment analysis, which has been very popular in recent years, is based on people's habits of expressing emotions, sharing opinions, and discussions through social media, and is a data mining technique used to measure a consumer's emotional state and attitude towards a particular topic (Sailunaz & Alhajj, 2019; Gitto & Mancuso, 2017). Sentiment analysis is a subfield of artificial intelligence that uses natural language processing and machine learning techniques to explain and classify thoughts and emotions from subjective data (Hasan et al., 2018). The primary function of sentiment analysis is determining what people think about specific topics and their opinions (Yu et al., 2013).

There are two different approaches for sentiment analysis, one is machine learning, and the other is a dictionary-based semantic approach. The dictionary-based semantic approach is made by determining the emotional loadings of words according to a dictionary with predefined meanings. In the machine learning method, on the other hand, the data needs to be trained by classifying the data as positive, negative, or neutral and extracting the features (Hasan et al., 2018). The training set needs to be created to build text-based models that use machine learning techniques as parameters in automatic data analysis. Semantic

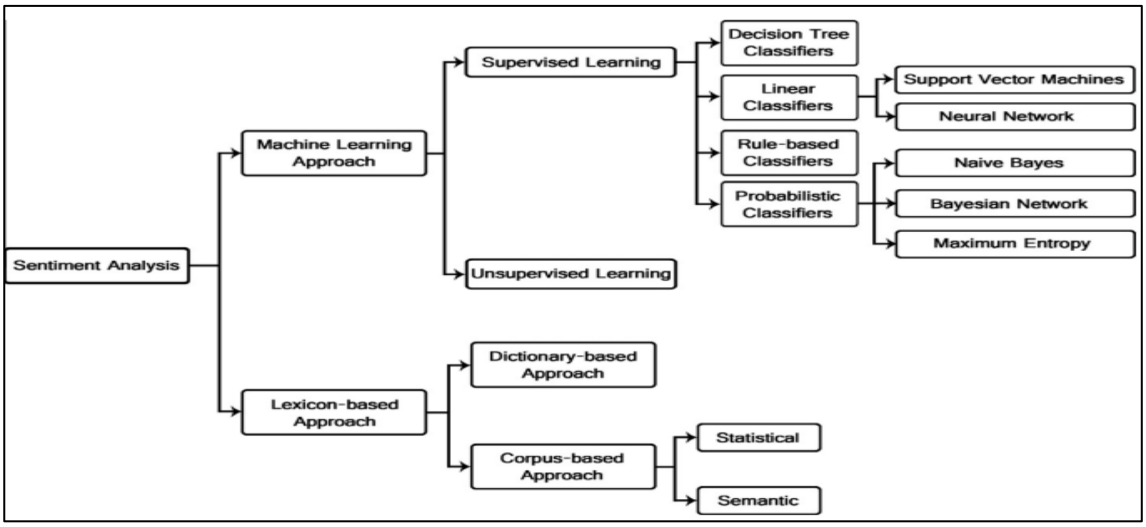


__Figure 1.__ Sentiment classification techniques (Medhat et al., 2014)

orientation involves applying a pre-generated set of positive and negative words, and sentiment analysis determines how often these terms are used in sentences (Ghiassi et al., 2013).

Figure 1 shows the classification of sentiment analysis techniques (Medhat et al., 2014). Twitter, which has Web 2.0 internet features, is defined as a social networking site by some authors and a micro-blogging site by others. Twitter, founded in 2006, is an online website where users open a post called a tweet, usually limited to 140 characters, to other users and where information is shared formally and informally (Flores & Rezende, 2018). Twitter is the social media site most used by government officials (Mainka et al., 2014).

The number of users on social media sites reaches billions. The content users create is very high and contains elements that make it difficult to process. Content such as texts, photos, and videos created by users on social networks constitute heterogeneous data (Yang et al., 2014). Since this content is increasing daily and is heterogeneous, it is difficult to understand and analyse. Due to this massive volume of data, there are challenges for natural language processing and categorising content into topics, associating them with quality elements, and analysing them (King et al., 2013).

Twitter data is suitable for sentiment analysis because sentiment analysis is based on natural language processing. Twitter data is generally used in sentiment analysis studies. Figure 2 shows an example of a developed system for processing Twitter data in a cloud system and presenting it to the user (Tedeschi & Benedetto, 2015). An application interface key is needed to communicate with Twitter servers to collect Twitter data. The key is adapted and executed in programs used in data analysis, such as Python or R.

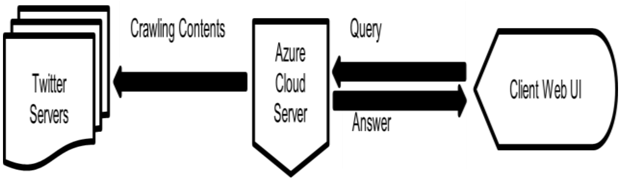


__Figure 2.__ Cloud system data processing (Tedeschi & Benedetto, 2015)

Text Mining

Text mining is the process of extracting hidden information from written data that does not have a straightforward form and formatting irregular data. Text mining results from joint research with natural language processing and information retrieval systems (Oğuzlar, 2011).

The techniques used in data mining are also used in text mining. Data mining relates to machine learning, statistics, database systems, information technologies, and visualisation (Cemaloğlu & Duykuluoğlu, 2020). Today, text mining is processing user-generated content from web pages or social media sites using information communication technologies with statistical science and natural language processing techniques using data mining steps. Due to the use of computer applications in text mining, computerised text analysis is also used in the literature (Artsin, 2020).

Text mining is used in situations such as creating the working logic of translation programs, analysing social posts, detecting plagiarism in scientific studies, analysing the speeches made by politicians, and determining the satisfaction levels or complaints of individuals (Altunkaynak, 2022).

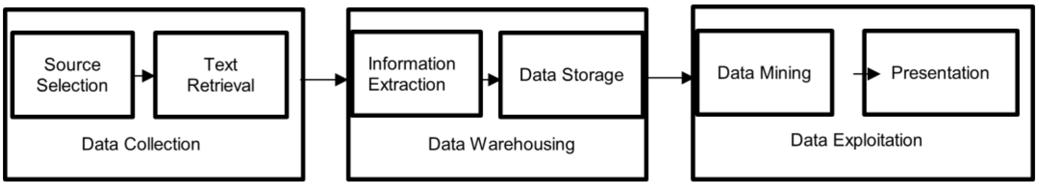


Figure 3. *Textual data mining process (Losiewicz et al., 2000)*

The text mining process is divided into three main steps: data collection, warehousing, and discovery (Losiewicz et al., 2000). The data collection step involves source selection and retrieval of text from the source. Source selection requires awareness of available sources, domain knowledge, and an understanding of the goals and objectives of data mining. Text selection is the process of discovering and retrieving texts from sources. This process can sometimes be done automatically or interactively by a domain expert. In data warehousing, the association is made with texts formatted as necessary for data storage and mining. This process saves the processed and associated texts and data models from facilitating further processing. The data discovery step consists of data mining and presentation steps. Data mining is the process of fitting models to data. The presentation phase is the process of assessing data quality, evaluating the appropriateness of the chosen model, and visualising the data mining results to support the interpretation of the model. Statistical results, syntax, and semantic inference are used to associate and make sense of texts.

Keywords, defined as a sequence of one or more words, can represent the content of a document. Keywords are frequently used to define queries in information retrieval systems because they are easier to identify, review, and remember (Rose et al., 2010). To achieve text mining objectives, methods such as word frequency, term frequency, word frequency, ranking, alignment, author recognition, and text classification are applied (Akyüz & Gülten, 2022). In text mining, keywords can represent the text from which they are extracted after being scored according to their frequency, degree of usage, and frequency ratio of their degree of usage.

In this study, tweets sent by tagging a municipality's Twitter account were classified according to term frequency and their relationship with each other. Service quality dimensions for the municipality were determined.

Service Quality

Quality is a concept that differs for products and services. The method of service delivery affects the service quality that customers perceive and expect when evaluating the quality of the service they receive (Meral & Baş, 2013). Service quality is a concept related to the ease of receiving service, the politeness of service providers, the business expertise and knowledge of employees, their ability to put themselves in the customer's shoes, and the extent to which customer needs can be met (Kayan Ürgün & Çilingir Ük, 2022).

In order to provide quality service, it is necessary to understand what the customer expects. The determinant of the customer's perception of service quality and satisfaction is their expectations. For this reason, learning customer expectations in service delivery is essential. Measuring the level of meeting the expectations of the service offered and making the necessary interventions in cases where it does not meet the expectations provides a competitive advantage (Mutlu & Ermeç Sertoğlu, 2018). Measuring service quality is essential for success (Jun et al., 1998).

It is stated that high service quality will provide more customer satisfaction, and service quality is directly related to customer satisfaction (Ramanathan & Karpuzcu, 2011). Providing excellent service quality that results in high levels of customer satisfaction is extremely important and a significant challenge for service industries (Hung et al., 2003).

There are different approaches to service quality measurement in the literature. Service quality measurement studies start with the Grönroos model developed by Grönroos in 1984. The SERVQUAL model was developed by Parasuraman, Zeithaml and Bery in 1985, and the SERVPERF model was developed by Cronin and Taylor in 1992; the model was developed by Dabholkar, Thorpe and Rentz in 1996 to measure the service quality of retail stores, There are various models such as the hierarchical approach model developed by Brady and Cronin in 2001, the E-TailQ model developed by Wolfinbarger and Gilly in 2003 for the online retail sector, and the E-S-QUAL model developed by Parasuraman, Zeithaml and Malhotra in 2005 for electronic services (Akıncı et al., 2009).

There are ten dimensions in the SERVQUAL service quality measurement model (Parasuraman et al., 1985). These elements are; "Reliability", which includes the concepts of billing, keeping records, performing the service on time, "Eagerness", which includes the attitude of serving the customer, "Competence", which includes having the necessary equipment to fulfill the service, "Access", which includes the appropriate working hours, the availability of the service, the waiting time to receive the service, "Courtesy", which includes the staff being polite in communication, and the explanation of the service, "Communication", which includes the interaction with the customer in situations such as specifying the cost; "Credibility", which includes the reputation, credibility and honesty of the organization; "Security", which includes physical, financial security and confidentiality; "Understanding/Knowing the Customer", which includes understanding the customer's specific needs; and "Tangibles", which includes the appearance of the staff, the physical plant and the tools and equipment used to provide the service. In their later studies, these ten dimensions were discussed in five dimensions: tangibles, reliability, enthusiasm, assurance, and empathy. In the Grönroos service quality model, technical and functional quality is considered in two dimensions, expected and perceived (Grönroos, 1984). Researchers who stated that the SERVQUAL model could not fully measure service quality by claiming that the customer will not have any expectations without using the product proposed the SERVPERF model (Cronin & Taylor, 1992).

Similarly, different service quality measurement models exist for different sectors in the literature. Some of these models have emerged by re-adapting the dimensions of the SERVQUAL Service Model to the sectors, while others have emerged by adopting the Grönroos Service Quality Model. Some service quality models have also been developed by linking service product, service delivery and service environment (Brady & Cronin, 2001).

Compared to the past, expectations in public services have increased, and citizens evaluate these services by comparing them with the services provided by the private sector (Sezer, 2008). Citizens' expectations of performance, quality, and transparency in public services have led to the new public administration approach. Performance measurement in public administration and applying private sector techniques are seen as a requirement of the new public administration approach (Eryılmaz, 2013). In recent years, reasons such as the increase in citizens' demands and expectations and the discussion of good management practices in the public sector require public administration to provide quality services (Hood & Dixon, 2013). For this reason, service quality has become an essential factor for public services. In the literature, service quality measurements related to public services have been made on health services, municipalities, nursing homes, and higher education institutions (Ay & Büyükkeklik, 2016). Many researchers have used the SERVQUAL service quality scale in their studies (Filiz et al., 2010; Gümüşoğlu et al., 2003; Usta & Memiş, 2010; Mbassi et al., 2019; Yildirim et al., 2019).

The fact that the SERVQUAL service quality model focuses only on process quality does not make comparative service quality measurement and that researchers working on service quality measurement in the literature state that quality dimensions should be changed for different business areas show that this service quality measurement model is not fully adequate (Ramanathan & Karpuzcu, 2011).

There are different definitions and approaches to service quality measurement in the literature. Researchers make various suggestions for the development of service quality measurement models. Most of the proposed models are based on classical questionnaires and scales, and data collection and implementation are disadvantageous in terms of time and cost. Today's technology offers various opportunities to use artificial intelligence-assisted techniques. Data and analysis techniques generated by users on social media provide the necessary infrastructure for creating new service quality measurement models. Figure 4 shows a proposal for service quality measurement using social media data (Duan et al., 2016).

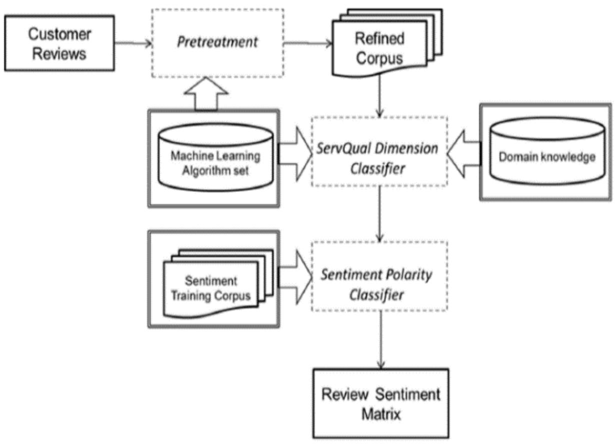


Figure 4. *Service quality measurement with sentiment analysis (Duan et al., 2016)*

When the studies are examined, it is seen that it is possible to measure service quality with sentiment analysis. In contrast to Duan et al. (2016), Martin-Domingo et al. (2019) and Lee et al. (2021), in this study, the words were determined from social media posts created by people using municipal services.

Method

The study seeks to answer how to develop a service quality measurement model from social media data processed with sentiment analysis and text mining methods. Twitter was preferred in the study because official institutions, organisations, political parties, and municipalities also prefer Twitter in social media communication and its usage rates. Local people express their opinions through tweets due to the service they receive. The research aimed to reach a rich sample of data by collecting Twitter data between 01.01.2016 and 30.04.2022. To collect historical data on Twitter, an academic research application is required.

For this reason, a project application named "Analysis of social media accounts of Municipalities with artificial intelligence" was made on Twitter. Thus, an academic application key was obtained, which allowed the collection of 10 million tweets per month for data collection. In the specified date range, 109.844 tweets were obtained by tagging a municipality's Twitter account with the Python program. Tweepy library is used to get data from Twitter in the written Python program. The obtained tweets were subjected to sentiment analysis using Azure Language services. In addition, the related tweets were analysed by text mining methods with MAXQDA, and service quality dimensions for the municipality's water and sewerage services were identified. To identify service quality dimensions, a keyword study was conducted by considering The Municipal Law No. 5393 and The Metropolitan Municipality Law No. 5216 which regulate the powers and responsibilities of municipalities.

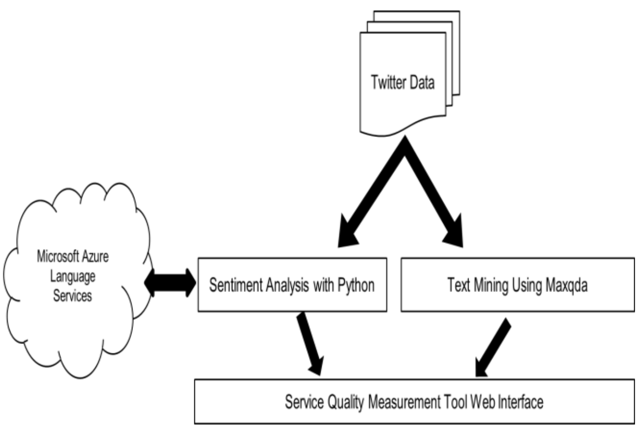


Figure 1. *Service quality measurement model system design*

The necessary Language Services have been created on Microsoft Azure to process the data coming from Twitter with sentiment analysis on the cloud platform. This language service performs sentiment analysis with the model developed by Microsoft with a supervised machine-learning technique on 01.10.2022.

A program written in Python in the Anaconda Navigator compiler sends relevant Tweets to the Microsoft Azure platform.

Using sentiment analysis, it scores the Tweets as positive, negative, and neutral. Scored Tweets are tagged and saved in the computer environment. The F1 score of the model used was calculated as 0.82692. Figure 5 illustrates the working system of the service quality measurement model.

Microsoft Azure Language Services performs tagging, as shown in Table1, during sentiment analysis. If a Tweet contains more than one sentence, it scores each sentence separately according to its sentiment and then labels it according to the overall average.

Table 1. Microsoft Azure Language Services Sentiment Analysis Method

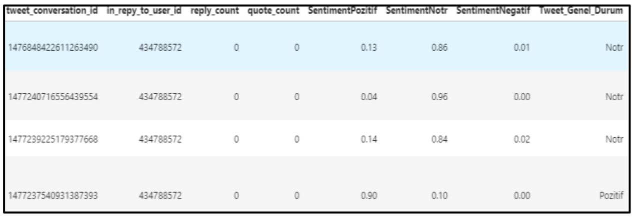
Sentence sentiment	Returned document label
At least one positive sentence is in the document, and the rest are neutral.	Positive
At least one negative sentence is in the document, and the rest are neutral.	Negative
All sentences in the document are neutral.	Neutral

Tweets sent by tagging the Twitter account of the municipality are analysed in Table 2.

Table 2. Example of Tweet sentiment analysis

Sample Tweet	Positive Score	Negative Score	Neutral Score	Tweet Label
"@ankarabbld Aski 0312 616 23 54 has not answered for days... who should I complain to? Help me please..."	0,0	0,87	0,13	Negative
"@ankarabbld We request that the necessary action be taken to eliminate the danger posed by the sewage pit next to the foot of the overpass in the Istanbul direction of the Istanbul Road metro stop."	0,06	0,2	0,74	Neutral
"@ankarabbld @askiankara @mansuryavas06 Hey mashallah how beautiful it is raining thank God"	0,62,	0,27	0,11	Positive

With the Python program, as shown in Figure 6, Tweets were retrieved from Twitter at one-month intervals, and sentiment analysis was performed.



tweet_conversation_id	in_repy_to_user_id	reply_count	quote_count	SentimentPozitif	SentimentNotr	SentimentNegatif	Tweet_Genel_Durum
1476848422611263490	434788572	0	0	0.13	0.86	0.01	Notr
1477240716556439554	434788572	0	0	0.04	0.96	0.00	Notr
1477239225179377668	434788572	0	0	0.14	0.84	0.02	Notr
1477237540931387393	434788572	0	0	0.90	0.10	0.00	Pozitif

Figure 2. Processing tweets in Python

In the data from Twitter, 3186 words that do not concern the quality of service dimensions, such as advertising links, irrelevant person, and topic tagging, which may cause interference in text mining with MAXQDA, were excluded from providing better results in text analysis. With the exclusion of parasitic words, 109.844 Tweets were divided into 865,261 words. From the 865.261 words, the keywords “flood”, “meter”, “rain”, “irrigation”, “infrastructure”, “sewage”, “drainage”, “maintenance hole”, “aski”, “waterless”, and “water” related to municipal water and sewerage services were extracted. Five thousand seven hundred sixty-six tweets with these keywords were coded, as shown in Figure 7.

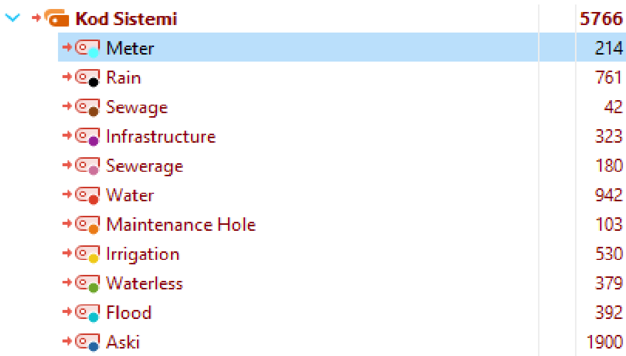


Figure 7. MAXQDA Code System

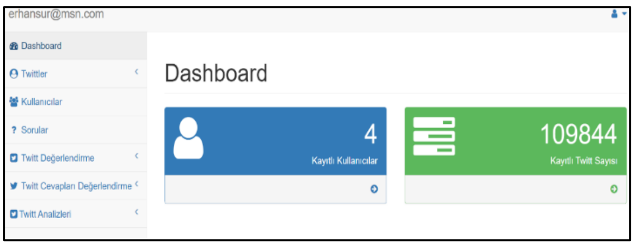
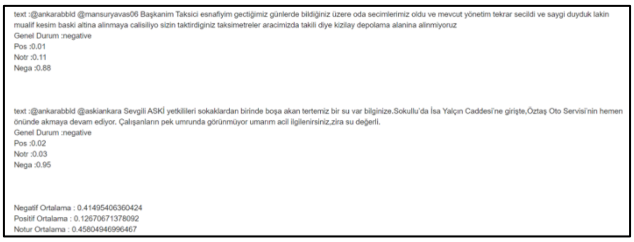


Figure 3. The web interface of the service measurement tool

The web interface can be re-tweeted anytime, and different authorised users can also use the platform. Figure 9 shows an example of the analysis of the keyword aski, which constitutes the municipality's water and sewerage service dimension.



text :@ankarabbld @mansuryavas06 Başkanim Taksici esnafiyim gectiğimiz günlerde bildiğiniz üzere oda secimlerimiz oldu ve mevcut yönetim tekrar secildi ve saygi duyduk lakin mualif kesim baski altina alinmaya calisiliyo sizin taktirdiginiz taksimetreler aracimizda takili diye kizilay depolama alanina alinmiyoruz
Genel Durum :negative
Pos :0.01
Notr :0.11
Nega :0.88

text :@ankarabbld @askiankara Sevgili ASKİ yetkilileri sokaklardan birinde boşa akan tertemiz bir su var bilginize.Sokullu'da İsa Yalçın Caddesi'ne girişte,Öztaş Oto Servisi'nin hemen önünde akmaya devam ediyor. Çalışanların pek umrunda görünmüyor umarım acil ilgilenirsiniz,zira su değerli.
Genel Durum :negative
Pos :0.02
Notr :0.03
Nega :0.95

Negatif Ortalama : 0.41495406360424
Positif Ortalama : 0.12670671378092
Notur Ortalama : 0.45804946996467

Figure 4. *Aski keyword analysis example*

Results and Discussion

When the literature is examined, it is seen that service quality measurement tools such as SERVQUAL and SERVPERF applied for businesses are also applied for municipalities. social media and internet technologies, which are widely used, have started to be used in service quality measurement for various sectors. It is recommended that the methods applied by businesses to be more successful should also be applied in public services as a requirement of the new public administration approach.
The studies show that social media data can measure service quality for various sectors. In this study, unlike other service quality measurement models, it is proposed to determine the service quality dimensions from the Tweets using the text mining method by considering the frequency of terms and the relationship between terms. When the Tweets tagged with a municipality were analysed, a total of ten dimensions were identified: funeral services, agricultural services, fire brigade services, water, and sewage services, social services, construction waste disposal services, police services, road maintenance and repair services, zoning services, and transportation services. The keywords flood, meter, rain, irrigation, water, infrastructure, sewerage, sewer, maintenance hole, waterless, and aski constitute the dimension of water and sewerage services. Water and sewerage services are discussed in the research.

Table 3. Average scores for the keywords water and sewerage service quality

Keyword	Frequency	Negative Mean Score	Positive Mean Score	Neutral Mean Score
Flood	392	0,41	0,14	0,45
Meter	214	0,66	0,09	0,25
Rain	761	0,63	0,09	0,28
Irrigation	530	0,59	0,1	0,31
Water	942	0,5	0,11	0,39
Infrastructure	323	0,60	0,1	0,3
Sewerage	180	0,68	0,06	0,26
Sewage	42	0,57	0,1	0,33
Maintenance Hole	103	0,51	0,11	0,38
Waterless	379	0,56	0,08	0,36
Aski	1900	0,42	0,12	0,46

The Maxqda programme shows the relationship between words in qualitative data analysis. It creates visual maps according to the position and co-occurrence of words (Guetterman & James, 2023). The frequency of co-occurrence of the keywords identified in Table 3 and their relationships with each other are shown in the map created in the MAXQDA program, as shown in Figure 10. The relationship table frequencies of keywords are also given in Table 4.

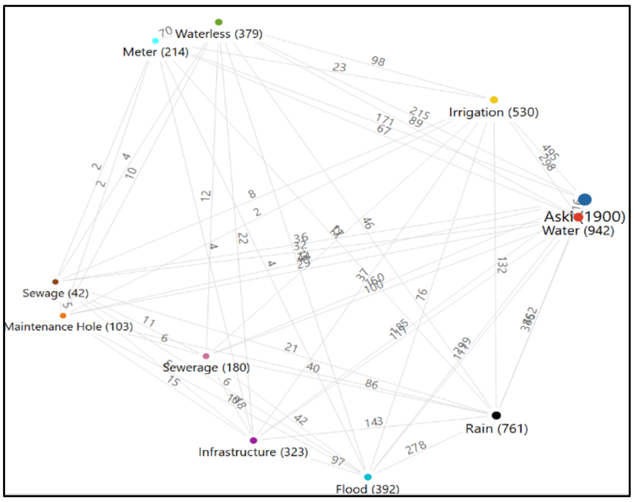


Figure 10. *Water and sewerage services keyword relationship map*

The distribution of 5766 tweets according to keywords is shown in Figure 11. According to

Figure 11, the word aski constitutes 33% of the service quality dimension. This word represents the relevant general directorate where water and sewerage services are provided.

Table 4. *Frequencies of keywords*

	Meter	Rain	Sewage	Infrastructure	Sewerage	Water	Maintenance Hole	Irrigation	Waterless	Flood	Aski
Meter	0	17	2	4	0	67	2	23	70	4	171
Rain	17	0	21	143	86	386	40	132	46	278	452
Sewage	2	21	0	5	11	32	5	8	4	6	36
Infrastructure	4	143	5	0	48	117	15	37	22	97	185
Sewerage	0	86	11	48	0	100	6	32	12	42	160
Water	67	386	32	117	100	0	29	298	89	111	716
Maintenance Hole	2	40	5	15	6	29	0	2	10	10	44
Irrigation	23	132	8	37	32	298	2	0	98	76	495
Waterless	70	46	4	22	12	89	10	98	0	15	215
Flood	4	278	6	97	42	111	10	76	15	0	299
Aski	171	452	36	185	160	716	44	495	215	299	0

The distribution of 5766 tweets according to keywords is shown in Figure 11. According to Figure 11, the word aski constitutes 33% of the service quality dimension. This word represents the relevant general directorate where water and sewerage services are provided.

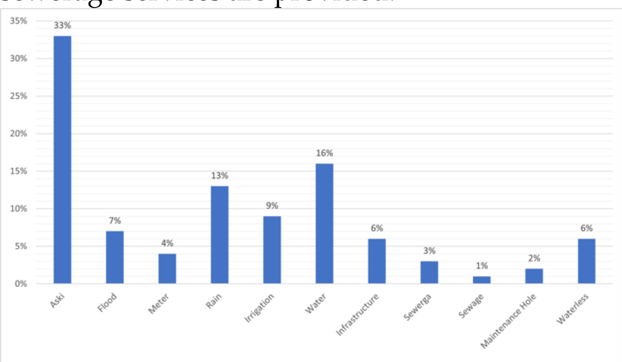


Figure 5. *Water and sewerage service keyword percentage distribution*

Positive, negative, and neutral ratings of keywords are shown in Figure 12.

Of the Tweets obtained, 1922 were labelled as negative, 973 as positive, and 2871 were neutral. The average negative score of the Tweets was 0.51, the average positive score was 0.11, and the average neutral score was 0.38. The percentage of sentiment tags for the analysed Tweets is shown in Figure 13.

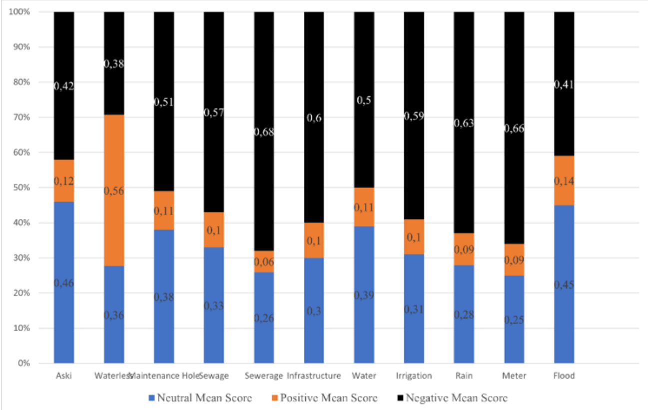


Figure 6. *Keyword Sentiment Score Averages*

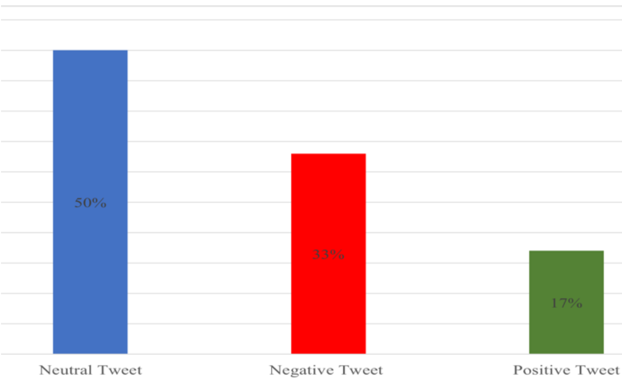


Figure 7. *Percentage of sentiment tags*

Conclusion

This study proposes a service quality model that can be made with text mining and sentiment analysis methods using social media data instead of survey-based service quality measurement models. In addition to the service quality measurement models with sentiment analysis encountered in the literature, the text mining method is added to determine the service quality dimensions. Thus, a sector-specific measurement model can be presented by identifying keywords that are directly related to the service itself, which are revealed by text mining.

In the service quality measurements in the literature, service quality is measured according to the five dimensions of SERVQUAL and SERVPERF models. The proposed model determined ten dimensions related to the powers and responsibilities of the municipality and 11 keywords related to water and sewerage services.

The proposed service quality model enables the municipality to evaluate its services and plan better for the services it will perform. The fact that the data collection method of the proposed service quality measurement model is effective makes the model flexible and advantageous.

In the application part, the water and sewerage services of the municipality are discussed. With the same model, the quality of other services of the municipality will be tried to be measured, and a comparison will be made. With the developed Web interface, this model will be used for different sectors.

Conflict of Interest Statement

The authors declare that there is no conflict of interest between them.

Researchers' Contribution Rate Declaration Summary

The authors declare that they have contributed equally to the article.

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