Journal of Innovative Transportation, 4(1), 17-24

Research Article

JOURNAL OF INNOVATIVE TRANSPORTATION

e-ISSN: 2717-8889

A natural language processing framework for analyzing public transportation user satisfaction: a case study

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Highlights

- User comments in public transport have been evaluated
- Improve service quality based on public transport user comments
- Natural language processing techniques improve public transportation services

Abstract

Public transportation services make an important contribution to the nation's economy. However, the public transportation system was significantly impacted both during and after the Covid-19 outbreak. To minimize these impacts, it is important to know the users' sentiment and improve the service quality accordingly to change the users' attitude towards public transportation systems. Natural language processing is used to make meaningful inferences about user sentiment using various analysis techniques. Historically, surveys have also been used for years to learn users' opinions about transportation services. In this study, this traditional method was used to determine the satisfaction of public transportation users. The categorization model employed in the system developed as part of this work is based on algorithms such as Long Short-Term Memory (LSTM), Random Forest (RF), and Multi Logistic Regression (MLR). The dataset contains information gathered from the online survey. Of the models created utilizing the training dataset, it was discovered that the LSTM model offered the highest accuracy. Users' comments can help improve public transportation operators' operations, improve service quality, and monitor actions accordingly. Therefore, in this study, users' emotions were classified as positive, negative, or neutral based on the comments.

Keywords: *Public transportation, service quality, natural language processing, sentiment analysis, machine learning*

Information

Received: 31.03.2023

Received in revised: 15.05.2023

Accepted: 30.05.2023

1. Introduction

Urban public transport contributes €130-150 billion per year to the EU economy [1]. However, in recent years, the number of public transport users has been negatively affected by the impact of Covid-19. Public transport also suffered a loss of income as people gave up travel [2]. At this stage, it is necessary to find out what people think and feel about public transport and encourage them to travel again. Analyzing the opinions of urban system users is an important step for sustainable cities [3]. With the developments in these natural language processing techniques, it has become possible to do opinion mining on people's comments [4]. Sentiment analysis, one of the prominent fields of study, uses natural language processing to interpret a text and classify it as positive or negative [5]. Researchers use social networks to determine comments and general perceptions about a topic [6-7]. However, since every user does not use social media and does not explain their views on public transport, the data is limited and it is very difficult to reach the opinions of public transport users. Surveys have long been used as a customary technique to assess people's satisfaction with transportation services.

In this paper, Turkish comments on an online questionnaire were studied using natural language processing techniques. A web interface was developed to label the collected comments and we labeled the comments. Word representation techniques were used to convert the words in the labeled comments into vectors, which were then used as an introduction to

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https://doi.org/10.53635/jit.1274928

supervised and unsupervised machine learning algorithms. The study encountered the following problems:

- The process of data collection in the online questionnaire is comparatively slow. As a result, only the users whose comments were collected were used.
- Turkish is an agglutinative language and as such has a significantly different structure than English. It is important to examine Turkish word suffixes as well.
- For Turkish, there are only a limited number of pre-trained word embeddings [8].

The n component hyperparameter, which denotes the number of clusters, is set to represent comments as an argument to the Sklearn library's "Linear Discriminant Analysis" class. The Least Squares Solution (LSQR) and Singular Value Decomposition (SVD) methods are supplied as parameters to the "solver" hyperparameter, which chooses the solver algorithm. The TF-IDF and word2vecword representation techniques are used to train the algorithm.

Moreover, this analysis can be useful for self-evaluation of operators to improve public transport operations, increase service quality, and adjust policies accordingly. Various analysis techniques are used to make meaningful inferences about people's different emotions. Passenger comments can help public transport operators improve their operations, improve service quality and set policies accordingly. In addition, with the analysis made in this study, the public transport operator can make self-evaluations according to the opinions of the passengers. Studies show that sentiment analysis technique is a method frequently used in the literature. It has been used in the analysis of social media comments, which are generally more accessible. In this study, the comments obtained as a result of the online survey conducted with the people who use the public transportation system were evaluated and it is very difficult to reach this information. The contribution of this study to the literature is that it shows the necessity of using user opinions as a data source in the online environment for medium-sized cities in determining public transportation satisfaction and making improvement decisions.

This paper consists of four main parts. The first part provides an overview of traditional public transportation opinion surveys and the application of NLP in transportation research. The second part explains the data extraction, data cleaning, and data processing used in this study. The third section analyzes the data and explains the results. In the last section, conclusions and suggestions for future work are presented.

2. Literature review

Sentiment analysis is a field of research that uses natural language processing and machine learning techniques to determine the mood or emotion expressed in a text. It involves determining subjectivity, polarity (positive or negative), and degree of polarity, and classifying the subject and author. Two main techniques used in sentiment analysis are the use of linguistic resources, where a value is assigned to each word, and machine learning techniques, which use counting methods to determine the sentiment of a text. Sentiment analysis has been used for a variety of applications, including social media, customer reviews, news articles, and survey comments.

There are numerous publications that evaluate public transportation using sentiment analysis [9]. He evaluated the enjoyment of Chicago rail passengers using data from Twitter. He proposed a two-sided evaluation methodology that considers both public opinion and indicators traditionally monitored by organizations. Similarly, public perception and sentiment regarding the Los Angeles light rail system was examined using data from Twitter [10]. In addition, Twitter data and news sources were used to assess public participation in transportation planning [11]. The Eglinton Crosstown transit project in Toronto was selected as a case study because it underwent extensive review after public participation.

The potential use of social media data to interact with citizens and customers using public transportation systems in rapidly growing cities is being investigated. Researchers used machine learning and natural language processing (NLP) techniques to model the topics, tone, and responsiveness of tweets about public transit performance in Sydney, Australia, and then compared them to information from a citizen survey of users. These interpretations proved effective for developing smart cities and gaining insights related to monitoring and improving transit performance [12].

The use of social and semantic network analysis, as well as sentiment analysis, was explored to understand the needs, motivations, and sensitivities of not only public transportation users, but also public transportation riders. In the study, the authors used data from the Twitter account of TransLink, a transit agency in Vancouver, Canada. The data was tracked over an 11-month period and compared to similar data from two other Canadian cities. The goal of the study was to compare results between days with traffic disruptions and days with normal operations. The authors developed a methodology to guide their research. First, they divided the social communities into small groups based on their connectivity and the topics they discussed. Second, they used a customer satisfaction glossary to identify themes in tweets. They observed the emergence of ideas by examining differences in topic and emotion [3].

Analysis of comments on various public transportation services in Shanghai using NLP techniques shows that people are more satisfied with transportation centers than with vehicles, and they are most satisfied with airports and least satisfied with busses. In addition, the NLP approach is regarded as transportation research that can be used to identify the strengths and weaknesses of the bus and improve the quality of public transportation services [13].

The Chinese government has implemented a digital health code system to detect possible exposure to COVID -19 and requires citizens to display the health code on their smartphones while using public transportation. The public was concerned about rumors of unfair treatment of elderly citizens who have difficulty obtaining a weight code and are therefore not allowed to use public transportation. This situation led people to have negative attitudes toward transportation services. In a research paper, a hybrid approach consisting of term frequency reverse document frequency, indirect Dirichlet allocation and sentiment classification was used to analyze messages from Sina Weibo, the Chinese version of Twitter, over a seven-month period. The results showed that older travelers were more positive about public transportation systems after the government backlash. The study advised government officials to explore new forms of automatic social control in future epidemics and to improve transportation policies in terms of equity and fairness [13].

300.000 tweets about transportation in Santiago, Chile, were analyzed. In this analysis, they categorized users by their mode of transportation and then predicted the relationships between mode of transportation, gender, and psycholinguistic dictionary categories. The concerns of women regarding transportation identified in the study are as follows:

Safety and security: Women expressed concern about the safety of their transportation options. They are concerned about sexual harassment and assault, and feel unprotected on public transportation, especially at night.

Emotional well-being: Women expressed more anger and sadness than expected and noted that they were more likely to experience negative emotions when using transportation. This may be attributed to the stress and inconvenience of commuting.

Accessibility: Women may face greater barriers to transportation due to their caregiving responsibilities, such as caring for children or elderly family members. They also tend to use public transportation more often, which may be less accessible than private transportation. Overall, the study suggests that transportation planners should consider the specific needs and concerns of women when designing transportation systems. In doing so, they can create more inclusive and safer transportation options for all users [14].

A study found that people in India, particularly in the Greater Mumbai metropolitan area, frequently share traffic information and location updates on Twitter, and the data was analyzed to identify traffic events and their locations. They used a new system that not only categorizes traffic-related tweets but also extracts location information from the content of the tweets. A support vector machine (SVM)-based model was used to categorize traffic-related tweets, which achieved the best performance. A hybrid georeference model combining a supervised learning algorithm with a set of spatial rules was used to extract location information from tweets. The authors believe that this information can be used to cost-effectively complement existing physical transportation infrastructure and help manage transportation services in urban environments. The study shows the potential of social media data as a source of information for understanding traffic events and managing transportation systems in developing regions where static sensors have limited spatial coverage and high maintenance costs [15].

A study was conducted to design bus routes using demand data obtained from social network data. For each of the 947 municipalities in the Barcelona region, a Twitter influencer score was created to extract public transportation demand data for a major music event in Barcelona (Canet Rock). This score provided a spatially distributed picture of demand for attending the event before purchasing tickets. Based on the demand data, the authors planned and implemented 11 new, commercially viable event bus routes that transported more than 450 additional passengers from urban areas and more rural areas of Barcelona to the music event. The study shows that data from social networks can be used to gain a better understanding of demand and support mobility management planning for major events. It can also help improve the ability of bus services to meet demand from urban environments and rural areas. Innovative use of social network data in transportation planning has the potential to improve mobility and accessibility, especially for underserved populations [16].

In summary, public transportation users can explore emotions and these emotions can guide the improvement of public transportation operations [3]. With the increasing use of websites to annotate transportation services and advances in natural language processing (NLP), sensitivity analysis is possible on a large scale and at low cost [4].

3. Study Area and Data Obtained

Isparta is a city in the Mediterranean region of Turkey known for its natural beauty, especially the many lakes and forests in the area. It is located about 130 kilometers northeast of the city of Antalya. The region has a Mediterranean climate characterized by hot, dry summers and mild, rainy winters. Isparta is also known for the production of roses and rose oil, which is an important industry in the region. It is also home to several universities and higher education institutions, making it an important educational and research center in the region.

In Isparta, buses are used as a public transportation system. An online survey of users of Isparta's public transportation system was done to gather the data, and in this survey, Turkish comment messages on the online questionnaire were analyzed using natural language processing techniques. At the end of the survey, users were asked to express their opinions and suggestions about the public transportation system. 310 of the 1584 users that took part in the poll gave their thoughts and recommendations. These opinions and suggestions were rated as positive, negative, and neutral using natural language processing analysis techniques.

4. Methodology

Natural Language Processing (NLP) is a field of study concerned with the interaction between computers and human language. There are several methods and techniques used in NLP to analyze and understand the text. These methods include tokenization, part-of-speech tagging, named entity recognition, sentiment analysis, machine translation, text classification, and information extraction. Tokenization involves breaking down text into smaller components such as words, phrases, or sentences. Part-of-speech tagging assigns each word in a sentence its grammatical part of speech (noun, verb, adjective, etc.). Named Entity Recognition is concerned with identifying and categorizing entities in text, such as people, places, organizations, and dates. The data will be split into training and testing data to build a classifier model, which will be evaluated using SVM and various kernels. The performance of the model will be assessed using a confusion matrix, which contains information on both actual and predicted categorization systems. Researchers often use accuracy, precision, recall, and F-measure matrices to evaluate the model [17]. Sentiment Analysis is concerned with the recognition, processing, and interpretation of feelings and emotions that people express with words [18]. Machine Translation involves the automatic translation of texts from one language to another. Text classification involves classifying texts into predefined categories based on their content. Information extraction involves extracting structured data from unstructured text, such as people's names and their contact information from resumes. These methods and techniques are often used in combination to develop more complex NLP systems and applications, such as chatbots, virtual assistants, and sentiment analysis tools. By using these techniques, NLP can help computers better understand and interpret human language, enabling a variety of useful applications in areas such as customer service, education, and healthcare. Example sentences in comments are given in Table 1.

Table 1. Example sentences in comments

Tone	Example Sentence
Positive	"In my opinion, it would make more sense to reduce the number of passengers on public transportation and increase the number of flights."
Negative	"Unfortunately, there are not enough rides and capacity on public transportation and we still have to squeeze in."
Neutral	"I hope that public transportation fees will be reduced or a subscription system for students will be introduced."

When applying natural language processing methods, there are some general steps to consider. First, in the problem definition phase, the specific natural language task to be performed must be determined, such as sentiment analysis, speech translation, or text classification. The relevant data is collected in text form and preprocessed by performing tasks such as cleaning, normalization, tokenization, and tagging of parts of speech. Then, the appropriate NLP method is selected. At this stage, a machine learning model trained on labeled data is used to perform sensitivity analysis. When using a machine learning model, it is necessary to train it on a labeled data set. This involves feeding the model with input data and correct outputs so that it can learn to predict the output for new input data. In the evaluation phase, the model is tested on a separate, labeled data set to determine how well it performs on new data. Measures such as precision, recognition, and F1 score are used to evaluate performance. Once you are satisfied with the performance of the model, you can deploy it in a production environment. This may include integrating it into an application, setting up an API, or using it as part of a larger system. The performance of the model is constantly monitored and you receive feedback. This helps identify areas for improvement and improve the model over time.

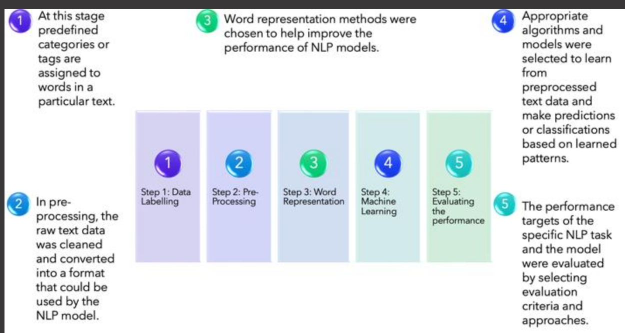

Figure 1. Steps of methodology

These are the general steps followed when using natural language processing methods. However, the specific steps and techniques used vary depending on the data. This study consists of 6 phases, and Figure 1 shows the phases of the methodology.

4.1. Data Labelling

In natural language processing, tagging text involves assigning predefined categories or tags to words or phrases in a given text. This process is also known as text annotation and is an important step in developing and training various machine learning models for natural language processing (NLP). To label the text in NLP, the categories to be assigned to the text are first determined. These are positive, negative and neutral emotions. A guide is created on how to identify and name the different categories. This guide includes rules for defining specific expressions, keywords, or phrases that correspond to each tag in the text. After annotating enough text, we used this data to train your NLP model. Various machine learning algorithms were applied to develop models that could automatically label new text based on patterns identified in the annotated data. The accuracy of the trained model was evaluated by comparing the predicted labels to the actual labels in a separate test dataset. Overall, text tagging is a critical process in NLP that enables the creation of a variety of machine learning models that can be used for a variety of applications, including sentiment analysis, text classification, and entity recognition.

4.2. Pre-Processing

Preprocessing is a crucial step in natural language processing (NLP) in which raw text data is cleaned and converted into a format that can be used by the NLP model. In this stage, irrelevant or unnecessary elements such as special characters and punctuation marks are removed from the text data. The goal is to clean up the text so that it can be processed more easily. This is an important step in NLP because most models are token-based. There are several ways to perform tokenization, including regular expressions, whitespace, or more complex algorithms. Blocking words are common words such as "and" that occur frequently in text data but do not have much meaning and are removed. Removing hidden words increases the efficiency and accuracy of NLP models. Stemming and lemmatization are techniques that reduce words to their root words, which helps to reduce the dimensionality of the data and improve model performance. In rooting, words are stripped of their suffixes, while in lemmatization, words are reduced to their base form. In the normalization phase, text data is converted to lowercase or numeric values are normalized. Another phase concerns misspelled words. In this phase, fuzzy matching algorithms were used to find words that are similar in meaning to the misspelled word. Negation is a common linguistic phenomenon in which the literal meaning of a word or phrase indicates its opposite. Consideration of negation in NLP is important for tasks such as sentiment analysis. For words that appear after a negation word, techniques such as emotion shift, in which the polarity of the emotion is reversed, are used. In general, preprocessing in NLP involves cleaning and transforming raw text data so that it can be used by the NLP model. The specific preprocessing tasks may vary depending on the type of text data and the NLP task to be performed [7].

4.3. Word Representation

Word representation methods are an important part of natural language processing (NLP) and help improve the performance of NLP models. Sentiment analysis was chosen, in which the text is processed before a word representation method is selected. The word representation method BagofWords (BoW), Term Frequency - Inverse Document Frequency (TF-IDF) and Word Indexing were determined to be suitable for the size of our dataset and available computational resources. Next, your text data is preprocessed, cleaned of raw text, and converted to a format that can be used by the word representation method. After selecting a word representation method and preprocessing the text data, the word vectors were created. Word vectors are a numerical representation of words that can be used in machine learning algorithms.

According to the BoW model, each word present in a text is regarded as a property, and its value is determined by how frequently it appears. Words are modeled using the BoW model as unigrams and bigram n-gram series. On the other hand, binary approaches used term weights independently. An n-gram receives a value of 1 in the binary method if it appears in the text, and a value of 0 if it does not.

A weighting method known as TF-IDF is based on multiplying the term frequency by the inverse document frequency. Equation (1) is used to generate this value, which is as follows:

$$TF * IDF = \frac{f(t,d)}{N} * \log\log(\frac{N}{1+n_t}) \quad (1)$$

Thus, t stands for the pertinent n-gram term, d for the pertinent text, $f(t,d)$ for the frequency of n-grams in the text, N for the total number of words in the document, and n_t for the number of different documents in which the term t (n-grams) appears [19-20]. As part of the word indexing process, a corpus was created using all the information. Each distinct word in this corpus was represented by a number.

Figure 2 shows the most used words. The most used words and the number of repetitions are given in the left-hand graphic, and the word cloud is given in the right-hand picture. Figure 3 shows the word cloud.

For example, word2vec generates a dense vector for each word in a corpus. Then, the NLP model is trained using machine learning algorithms with the generated word vectors. After the NLP model is trained, it is important to evaluate its performance on a separate test dataset. In summary, using word representation methods in NLP involves selecting an appropriate method for your particular task, preprocessing your text data, generating word vectors, training your NLP model, and evaluating and improving your approach.

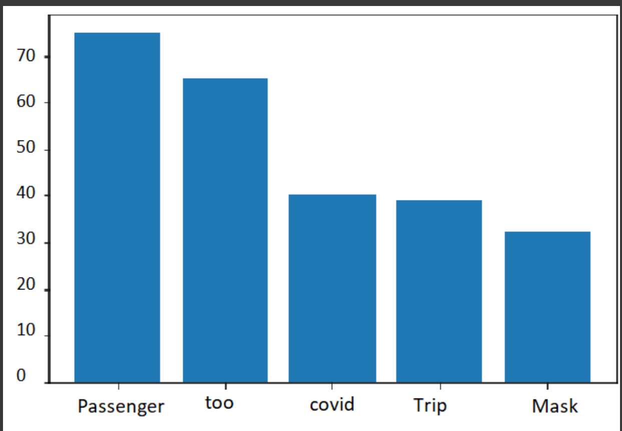

Figure 2. Most used words

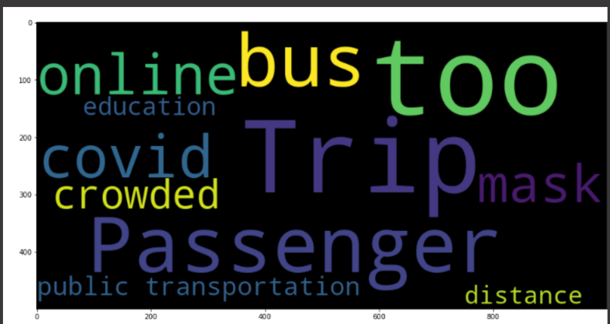

Figure 3. Word cloud

4.4. Machine Learning

The machine learning phase of natural language processing (NLP) involves the selection of appropriate algorithms and models that learn from preprocessed text data and make predictions or classifications based on the learned patterns. First, the preprocessed text data were converted into a numerical form that can be used by machine learning algorithms. Second, a model was selected that could be used for NLP tasks depending on the size of the data set and the complexity of the problem. Third, the model was trained on a labeled dataset where the input data and the corresponding output are known. The goal of training is to learn the patterns and relationships between input and output data. Most machine learning models have hyperparameters that must be set before training. The hyperparameters are values that determine the behavior of the model during training, such as the learning rate, regularization strength, and number of layers. Finding the optimal values of these hyperparameters is critical for good performance. In the evaluation phase, the model was evaluated on a test dataset after training to assess its performance. In general, the machine learning phase in NLP involves selecting an appropriate model, training it on labeled data, setting its hyperparameters, and evaluating its performance. The specific steps and techniques used may vary depending on the task and the size and complexity of the dataset.

4.5. Evaluating the performance

Evaluating the performance of natural language processing (NLP) models is essential to determine how well they perform on a given task. Common metrics and approaches for evaluating NLP models include accuracy, precision and recall, F1 score, confusion matrix, cross-validation, and human evaluation. The selection of evaluation metrics and methods depends on the NLP task and the model's performance goals. It is critical to consider the evaluation metrics and methods carefully to ensure that the model performs well and meets the task requirements.

Table 2. Classification Accuracy Rates and F1 score values

Dataset/Algorithm	Precesion	Recall	F1 Score	Accuracy
Dataset1/MLR	0.85	0.81	0.82	83.07
Dataset1/RF	0.86	0.83	0.84	84.24
Dataset2/MLR	0.82	0.79	0.80	80.91
Dataset2/RF	0.85	0.83	0.84	83.93
Dataset3/LSTM	0.84	0.84	0.84	84.46

The dataset used in this work was first vectorized individually using BoW, TF-IDF, and Word Indexing, and five different classifiers were then tested on it. The classification success rates are displayed in Table 2. Table 3 demonstrates that the Multinominal Logistic Regression (MLR) technique outperforms the Random Forest (RF) approach on Datasets 1 and 2. Also, it was discovered that the LSTM model on the set produced using the indexing method had the most success on the created data sets [20].

5. Results and analysis

By modeling the dynamics of travelers' opinions based on their relationships to each other and the issues they have in mind, transportation planners and operators can better tailor their planning and operational processes to user profiles. This could ultimately lead to increased use of public transportation and have a positive impact on sustainable development. The research study explores natural language processing to provide a better understanding of the views and satisfaction levels of public transport users. In the dataset used, a three-way classification was performed with positive, negative, and neutral labels.

The dataset for the LSTM model is divided into 20% test and 80% training data. The activation function "softmax" is used in the output layer of the model. In the model, which runs with 10 epochs, the data is given in batches of 512. Since the data is categorical, "categorical_crossentropy" was chosen as the loss function. A summary of the model used can be found in Table 3.

Table 3. LSTM Model Summary for 3 Labels Dataset [20].

Layer	Output Shape	Param#
embedding_1 (Embedding)	(None, 48,256)	128000000
lstm_1 (LSTM)	(None, 16)	17472
dense_1 (Dense)	(None, 3)	51
	Total params	128017557
	Trainable params	128017557
	Non-trainable params	0

After preprocessing to construct one of the three hashtags - positive, negative, or neutral (see Figure 4)- for each tweet, the 310 survey comment data generated for analysis was used as input to this model.

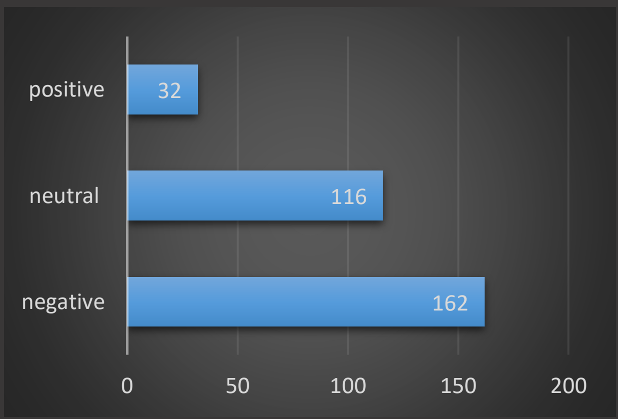

Figure 4. Distribution of comments by sentiment type

Examining Figure 2, it is clear that the majority of passengers have negative thoughts. The most frequently used words were "passenger", “too” and "crowd". Here "too" is used with too many passengers. In this situation, passengers complain about the low number of trips and the high number of passengers. The best proposed solution for the operators would be to increase the number of trips. If the number of trips is increased, the crowding in public transport will also decrease.

The online survey was applied to public transport users in a three-month period between November 2021 and January 2022. During preprocessing, blank data or data with only numeric information was eliminated. The Appendix contains the results of this pre-trained model. Participants include 51% males and 49% females. Male participants had more neutral thoughts than female participants, while female participants expressed both more negative and more positive emotions. In addition, 80% of the participants are between 19 and 30 years old and have completed high school.

6. Conclusions

Natural language processing techniques used to determine the thought or emotion expressed in a piece of text have paved the way for many innovative technologies, especially artificial intelligence. These studies are important for all businesses that want to serve people better. The public transport system is also a people-oriented system, and users' comments show the status of the operators. It is important to get the opinions of the passengers in order for the public transport operators to make their own self-evaluations. In this way, businesses can offer the service that passengers desire. In order to evaluate the opinions of the passengers with natural language processing techniques, online and regular opinions should be obtained. This may be qr codes placed on public transport vehicles or by connecting with the mobile application of the bus operator and expressing an online opinion. Improvements made by businesses based on these comments allow the system to provide better service. Field experience has shown that everyone talks but does not comment when we ask them to write the comments. New policies can be developed to support users' comments

This paper showed that the LSTM algorithm achieved an accuracy rate of 84.46%, showing that the results of this research deserve to be considered for upgrading public transport services. The operators decide on the system improvement method of the public transport system enterprises and the public transport users who are the main service providers are neglected. With this study, the improvements to be made in line with the feelings, thoughts and opinions of the users will enable the system to provide better service to the user. Thus, people are expected to prefer public transportation. In the current situation, the operating frequency ranges of the public transport system are considered sufficient and no regulation is made. However, the results of this study show that passengers complain of overcrowding. In this case, it is seen that the service quality should be increased with the improvement to be made in the public transport frequency ranges.

Declaration of Interest Statement

The author declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contribution Statement

All Authors contributed equally at all stages of the study.

References

[1] Union Internationale des Transports Publics. (2022). UITP Worldwide Europe. Last Accessed December 20, 2022. https://www.uitp.org/regions/europe/

[2] Kanda, W., & Kivimaa, P. (2020). What opportunities could the COVID-19 outbreak offer for sustainability transitions research on electricity and mobility?. *Energy Research &*

Social Science, *68*, 101666. https://doi.org/10.1016/j.erss.2020.101666

[3] El-Diraby, T., Shalaby, A., & Hosseini, M. (2019). Linking social, semantic and sentiment analyses to support modeling transit customers' satisfaction: Towards formal study of opinion dynamics. *Sustainable Cities and Society*, *49*, 101578. https://doi.org/10.1016/j.scs.2019.101578

[4] Liu, Y., Li, Y., & Li, W. (2019). Natural language processing approach for appraisal of passenger satisfaction and service quality of public transportation. *IET Intelligent Transport Systems*, *13*(11), 1701-1707. https://doi.org/10.1049/iet-its.2019.0054

[5] Öğe, B. C., & Kayaalp F., (2021). Farklı Sınıflandırma Algoritmaları ve Metin Temsil Yöntemlerinin Duygu Analizinde Performans Karşılaştırılması. *Düzce Üniversitesi Bilim ve Teknoloji Dergisi*, *9*(6), 406-416. https://doi.org/10.29130/dubited.1015320

[6] Collins, C., Hasan, S., & Ukkusuri, S. V. (2013). A novel transit rider satisfaction metric: Rider sentiments measured from online social media data. *Journal of Public Transportation*, *16*(2), 21-45. https://doi.org/10.5038/2375-0901.16.2.2

[7] Effendy, V., Novantirani, A., & Sabariah, M. K. (2016). Sentiment analysis on Twitter about the use of city public transportation using support vector machine method. *Intl. J. ICT*, *2*(1), 57-66. https://doi.org/10.21108/IJOICT.2016.21.85

[8] Taskin, S. G., Kucuksille, E. U., & Topal, K. (2022). Detection of Turkish fake news in Twitter with machine learning algorithms. *Arabian Journal for Science and Engineering*, *47*(2), 2359-2379. https://doi.org/10.1007/s13369-021-06223-0

[9] Schweitzer, L. (2014). Planning and social media: a case study of public transit and stigma on Twitter. *Journal of the American Planning Association*, *80*(3), 218-238. https://doi.org/10.1080/01944363.2014.980439

[10] Luong, T. T., & Houston, D. (2015). Public opinions of light rail service in Los Angeles, an analysis using Twitter data. *IConference 2015 Proceedings*.

[11] Nik Bakht, M., Kinawy, S. N., & El-Diraby, T. E. (2015). *News and social media as performance indicators for public involvement in transportation planning: Eglinton Crosstown Project in Toronto, Canada* (No. 15-0117).

[12] Lock, O., & Pettit, C. (2020). Social media as passive geo-participation in transportation planning–how effective are topic modeling & sentiment analysis in comparison with citizen surveys?. *Geo-spatial Information Science*, *23*(4), 275-292. https://doi.org/10.1080/10095020.2020.1815596

[13] Liu, X., Ye, Q., Li, Y., Fan, J., & Tao, Y. (2021). Examining public concerns and attitudes toward unfair events involving elderly travelers during the COVID-19 pandemic using Weibo data. *International Journal of Environmental Research and Public Health*, *18*(4), 1756. https://doi.org/10.3390/ijerph18041756

[14] Vasquez-Henriquez, P., Graells-Garrido, E., & Caro, D. (2019, June). Characterizing transport perception using social media: differences in mode and gender. In *Proceedings of the 10th ACM Conference on Web Science* (pp. 295-299). https://doi.org/10.1145/3292522.3326036

[15] Das, R. D., & Purves, R. S. (2019). Exploring the potential of Twitter to understand traffic events and their locations in Greater Mumbai, India. *IEEE Transactions on Intelligent Transportation Systems*, *21*(12), 5213-5222. https://doi.org/10.1109/TITS.2019.2950782

[16] Sala, L., Wright, S., Cottrill, C., & Flores-Sola, E. (2021). Generating demand responsive bus routes from social network data analysis. *Transportation Research Part C: Emerging Technologies*, *128*, 103194. https://doi.org/10.1016/j.trc.2021.103194

[17] Nurthohari, Z., Sensuse, D. I., & Lusa, S. (2022, July). Sentiment Analysis of Jakarta Bus Rapid Transportation Services using Support Vector Machine. In *2022 International Conference on Data Science and Its Applications (ICoDSA)* (pp. 171-176). IEEE. https://doi.org/10.1109/ICoDSA55874.2022.9862903

[18] Wang, S., Li, M., Yu, B., Bao, S., & Chen, Y. (2022). Investigating the Impacting Factors on the Public's Attitudes towards Autonomous Vehicles Using Sentiment Analysis from Social Media Data. *Sustainability*, *14*(19), 12186. https://doi.org/10.3390/su141912186

[19] Şahin, G. (2017). Turkish document classification based on Word2Vec and SVM classifier. In *2017 25th signal processing and communications applications conference (SIU)* (pp. 1-4). IEEE. https://doi.org/10.1109/SIU.2017.7960552

[20] Kemaloğlu N., Küçüksille E., and Özgünsür M. E. (2021). Turkish sentiment analysis on social media. *Sakarya University Journal of Science*, *25*(3), 629-638. https://doi.org/10.16984/saufenbilder.872227