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Analysing Social Media Discourse on Electric Vehicles with Machine Learning

Yasin Özkara [1], Yasemin Bilişli [2,*], Fatih Serdar Yildirim [3,*], Fahrettin Kayan [4], Agah Başdeğirmen [5], Mehmet Kayakuş [6] and Fatma Yiğit Açıkgöz [4]

[1] Department of Elementary Education, Faculty of Education, Akdeniz University, Antalya 07058, Türkiye; yasinozkara@akdeniz.edu.tr
[2] Department of Office Services and Secretariat, Social Sciences Vocational School, Akdeniz University, Antalya 07058, Türkiye
[3] Department of Mathematics and Science Education, Faculty of Education, Akdeniz University, Antalya 07058, Türkiye
[4] Department of Marketing and Advertising, Social Sciences Vocational School, Akdeniz University, Antalya 07058, Türkiye; kayan@akdeniz.edu.tr (F.K.); fatmayigit@akdeniz.edu.tr (F.Y.A.)
[5] Department of Management and Organisation, Isparta Vocational School, Isparta University of Applied Sciences, Isparta 32200, Türkiye; agahbasdegirmen@isparta.edu.tr
[6] Department of Management Information Systems, Faculty of Social and Human Sciences, Akdeniz University, Antalya 07800, Türkiye; mehmetkayakus@akdeniz.edu.tr
* Correspondence: yasemin@akdeniz.edu.tr (Y.B.); fsyildirim@akdeniz.edu.tr (F.S.Y.); Tel.: +90-532-728-0784 (Y.B.); +90-242-227-4400 (F.S.Y.)

Abstract: Social acceptance of electric vehicles is of great importance for environmental sustainability and economic development. This study aims to examine Turkish and English tweets about electric vehicles with sentiment analysis, text mining, and topic modelling techniques to reveal consumers' electric vehicle purchasing behaviours, consumer perception and acceptance processes about electric vehicles, and social perceptions. The data was taken from the X platform, and high accuracy and F1 scores were obtained in both languages in the classification made with the deep learning-based LSTM model. The accuracy was 92.1% for English tweets and 96.7% for Turkish tweets. According to the sentiment analysis results, the perception of electric vehicles is generally positive in both languages. However, while the rate of neutral sentiment is higher in Turkish tweets, the rate of negative sentiment is higher in English tweets. This indicates that there is more criticism and debate about electric vehicles globally, while Turkish tweets have more neutral views on the subject. Word frequency analysis shows that positive comments about electric vehicles focus on economic and environmental advantages, while negative comments include concerns about charging time, battery life, and range concerns. The topic modelling identified three main themes related to electric vehicles: (1) reasons for being preferred by consumers and their purchasing tendencies, (2) the role of brands, (3) market developments and marketing strategies. In Turkish tweets, electric vehicle production, charging infrastructure, and consumer purchasing trends were at the forefront. In general, it is emphasised that charging infrastructure should be strengthened, battery performance should be improved, and costs should be reduced to accelerate the adoption of electric vehicles.

Keywords: electric vehicles; consumer behaviour; marketing strategies; social media analysis; deep learning; information systems in marketing; sentiment analysis; artificial intelligence; marketing communication

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1. Introduction

Electric vehicles (EVs) have gained an important place among sustainable transportation alternatives in recent years [1]. Many governments and automotive companies are investing heavily in this technology because of its environmental benefits, such as reducing dependence on fossil fuels, lowering carbon emissions, and reducing air pollution [2–4]. However, society's adaptation and acceptance of this new technology vary depending on several factors. Social acceptance of electric vehicles is based on many factors, such as individuals' perceptions of the technology, their level of trust, cost analysis, and environmental awareness. At this point, social media platforms have become an important source where individuals freely share their opinions, express their experiences, and shape social perceptions [5].

This study aims to analyse the public's perspective on electric vehicles on the X platform (formerly Twitter). Social media is a valuable source of data that reveals what individuals think about current events and technologies. Within the scope of the study, 6000 English and 891 Turkish tweets posted in the last month were collected and analysed.

Frequent discussions on social media reveal critical challenges in the adoption of EVs, such as insufficient charging infrastructure, high initial costs, concerns over battery life, and limited government incentives. Range anxiety and the availability of reliable and fast charging stations are recurring issues among users. Additionally, uncertainties regarding battery replacement costs and the lack of a standardised charging network across regions continue to raise concerns. These topics reflect the real-world hesitations that shape public discourse and perceptions regarding EVs.

Using techniques such as text mining, sentiment analysis, and topic modelling, individuals' positive, negative, and neutral views on EVs were identified. The focus of this study is to reveal the differences between Turkish- and English-speaking consumers (electric vehicle users), to identify the prominent themes about EVs according to their moods, and to make important inferences about the adaptation process of society to this new technology.

Social media platforms, which have been of great importance in marketing communication in recent years, provide an environment where individuals express and discuss their views on EVs. Individuals contribute to the shaping of social perception by sharing their experiences, expectations, and concerns about EVs on social media. Determining societal attitudes towards EVs is critical for the future of this technology. Therefore, analysing the opinions shared on social media offers great potential to reveal social interest, concerns, and expectations for EVs.

While various studies have examined EV perceptions using surveys or interviews, very few have employed real-time social media data across different linguistic contexts [6,7]. This study uniquely contributes by combining sentiment analysis and topic modelling on a bilingual dataset, revealing differences in perception between Turkish and English-speaking users. Thus, the study fills an important gap by providing a cross-cultural perspective using machine learning techniques applied to public social media discourse. This study analyses the real-time comments of users on the X platform to reveal current debates and trends about EVs. Moreover, through a comparative analysis of Turkish and English tweets, differences in perceptions in different cultural and linguistic contexts are also examined. In this respect, the study makes important contributions not only to the acceptance process of EVs but also to consumer perception research based on social media analysis.

The comparative analysis also aims to highlight how cultural and linguistic factors may influence consumer sentiment, offering valuable implications for industry and policymakers. Using sentiment analysis and topic modelling techniques, users' positive, negative, and neutral views were classified, and corresponding themes were identified. The study

aims to assess the linguistic and cultural factors affecting the adoption of EVs, especially by revealing the differences between Turkish and English tweets. The findings will be an important resource for both policymakers and the automotive industry in developing strategies for the dissemination, marketing, and sales of EVs.

In addition to prior studies, recent works have contributed to the understanding of digital discourse surrounding EVs. For instance, Senyapar (2024) analysed social media sentiment towards EVs in Turkey, highlighting public concerns and engagement patterns [8]. Similarly, Dcosta et al. (2024) provided a comprehensive interdisciplinary review on EV adoption, identifying key behavioural and technological determinants [9]. These recent contributions offer valuable context to frame the present study.

2. Literature

Social acceptance of electric vehicles (EVs) is shaped by many factors, such as environmental sustainability, technological advances, infrastructure capabilities, and consumer perceptions. Previous studies on this topic have addressed different aspects that influence EV adoption.

In recent years, scholars have increasingly examined the social and psychological dimensions of EV adoption. For example, Senyapar (2024) explored digital discourse in Turkey, identifying how user sentiment on social media evolves over time [8]. Dcosta et al. (2024) conducted an interdisciplinary review of EV adoption, highlighting trends in consumer behaviour, policy, and infrastructure [9]. Furthermore, Perotti et al. (2023) examined why individuals share misinformation about EVs on social media, highlighting the role of perceived severity and vulnerability in influencing user behaviour. Their study emphasises that trust in information sources and susceptibility to fake news can significantly affect public perceptions of EVs and their adoption. These recent findings complement earlier literature by offering a behavioural explanation for the spread of misinformation, thereby strengthening the contemporary foundation for the present research [10].

Many studies emphasise the influence of economic factors on EV adoption. Sierzchula et al. (2014) analysed the strong influence of financial incentives on EV adoption and found that economic incentives are an important factor in determining consumer decisions [11]. Javid and Nejat (2017) examined the role of regional factors in the diffusion of EVs and showed that government policies and incentive programmes can accelerate this process [12]. Mukherjee and Ryan (2020) analysed the adoption trends of EVs in Ireland, examining the economic and infrastructural factors that influence consumers' decisions [13].

Other research focuses on consumer behaviour and psychological acceptance of EVs. Park et al. (2018) evaluated the place of EVs in the automotive industry and the social acceptance process [14]. Krishna (2021) identified the factors hindering the adoption of EVs using thematic analysis and found that charging infrastructure and range anxiety were particularly prominent [15]. Wicki et al. (2023), in a study evaluating consumers' knowledge about EVs, stated that incomplete data and misperceptions about the acceptance of EVs can negatively affect the process [16].

Charging infrastructure and range anxiety are also critical factors in the adoption of EVs. Burkert et al. (2021) examined concerns about the adequacy of EV charging infrastructure among consumers in Germany and showed that this factor may limit the diffusion of EVs [17]. Kim et al. (2017) analysed the impact of the range of EVs on consumer decisions and found that the interest in EVs increases with increasing range [18]. Wang et al. (2022) evaluated consumers' attitudes towards electric vehicle charging plans using a technology acceptance model [19].

Some research focuses on the social sustainability and social acceptance of EVs. Sovacool (2017) conducted a study assessing the impact of expert opinions and theories on

the diffusion of EVs [20]. Omahne et al. (2021) analysed how EVs are linked to sustainable development goals [21]. Tyagi and Vishwakarma (2022) emphasise that EVs should be evaluated in terms of social sustainability [22]. Schlüter and Weyer (2019) showed that electric vehicle sharing services can accelerate the adoption of EVs by consumers [23].

There are also studies evaluating the impact of EVs on consumer perceptions. Shanmugavel et al. (2022) analysed the adoption of EVs within the framework of social comparison theory and the technology acceptance model [24]. Huang et al. (2021) developed a model that evaluates the adoption of EVs in the Chinese market [25]. Priessner et al. (2018) analysed the factors influencing adoption among drivers of potential EVs in Austria [26].

To provide a systematic foundation for the current study, it is important to consider established theories such as Rogers' Diffusion of Innovation Theory and the Technology Acceptance Model (TAM). The Diffusion of Innovation framework explains how new technologies are adopted across social groups over time, influenced by factors such as relative advantage, compatibility, and observability [27–29]. TAM focuses on how perceived usefulness and ease of use affect individuals' intentions to adopt new technology. These frameworks have been widely used to understand consumer adoption of EVs and offer a theoretical lens through which social media discourse can be interpreted.

This study examines the social acceptance of EVs through Turkish and English tweets shared on the social media platform X in the last month. While most of the previous studies rely on survey and experimental methods, this study analyses the public's real-time perceptions using social media data. Moreover, by using AI-based text mining methods such as sentiment analysis and topic modelling, a more comprehensive framework of consumers' opinions about EVs is presented. Specifically, it was found that while English tweets showed a more positive attitude towards EVs in general, Turkish tweets highlighted more concerns, such as charging infrastructure and cost. In this context, the study contributes to the literature by revealing how EVs are perceived at the global and local levels.

Prior studies have employed various machine learning models for sentiment analysis, including support vector machines (SVM), naive Bayes, decision trees, and deep learning architectures such as CNNs and LSTM. While traditional models offer faster training times and interpretability, they often struggle with contextual nuances. Deep learning models, particularly LSTM and transformers, have shown higher accuracy in capturing complex linguistic patterns [30,31]. However, LSTM models may require large datasets and longer training times [32,33]. Our study uses the LSTM model due to its proven effectiveness in sequential data processing and its suitability for tweet-based sentiment analysis.

3. Materials and Methods

In this study, tweets about EVs shared from the X platform via API in the last month were collected and analysed. A total of 6000 English and 891 Turkish tweets were analysed using sentiment analysis and topic modelling techniques. In the process of analysing the tweets, text preprocessing techniques were first applied, unnecessary words were removed, and the data were made ready for analysis.

In the sentiment analysis phase, tweets were classified as positive, negative, and neutral using deep learning-based models. The results showed that 417 of the Turkish tweets contained positive, 140 negative, and 301 neutral sentiments, while 2486, 1086, and 1796 of the English tweets contained positive, negative, and neutral sentiments, respectively.

Using the topic modelling method, the most frequently discussed themes related to EVs were identified according to mood. This analysis reveals under which main headings the perception of EVs is grouped in line with positive, negative, and neutral views.

3.1. Dataset

In this study, data were collected from the social media platform X (formerly Twitter) to examine public perception towards EVs. The main reason for choosing the X platform is that it has a large and diverse user base who can freely share their opinions on current events and technologies. In addition, the X platform provides an environment conducive to analysing social trends and debates due to its real-time and dynamic data flow [34]. The dataset used in the study was created from tweets posted within the last month through the X API. The one-month data collection period was specifically chosen to reflect the current and dynamic public perceptions about EVs. During this period, the tweets about EVs constituted a representative sample to better analyse the current views and trends of society.

The collected dataset consists of 6000 English and 891 Turkish tweets. In the data analysis process, unnecessary characters, duplicate data, and meaningless expressions were removed in the text preprocessing stage; in addition, only the content that provided semantic integrity was used in the analysis. As a result of the cleaning process, the number of English tweets decreased to 5370, and the number of Turkish tweets decreased to 858. The resulting dataset was used in the sentiment analysis and topic modelling stages, contributing to the determination of public perception of EVs.

The final dataset used in the study consisted of 5370 English and 858 Turkish tweets after preprocessing. While this dataset provides a rich and diverse source of user opinions, it may also carry potential biases. For instance, certain demographic groups (e.g., younger, tech-savvy users) may be over-represented on social media platforms like X. Additionally, users expressing strong opinions are more likely to post about EVs, possibly skewing the dataset toward more polarised views. These limitations were considered during analysis and interpretation.

The sample dataset is shown in Table 1.

Table 1. Sample dataset.

Tweet	Language
Fully EVs are impractical for most people and will be replaced by some form of hybrid technology in the not-too-distant future.	Tr
Don't buy an electric car, it explodes in an accident	Tr
I have a question for electric vehicle owners, let's say the charging time is 1 h or there is a queue, isn't that annoying?	Tr
If you want more EVs to be sold, you need to increase the penalties and sanctions against friends who park in front of charging stations. Otherwise, many people will not invest in EVs in this way. A scenario where charging is a problem would scare everyone.	Tr
The electric car market is moving very fast, although it is stressful, slowly everyone is looking hot	Tr
Visited China last year. Their electric car offerings are better, from a local perspective. More of the features they care about, significantly cheaper, better compatibility with charging stations, etc.	En
Electricity much cheaper than gasoline. Thanks for making electricity cheaper. It makes driving an electric car even better now!	En
Shifting gears from speed to sustainability, the high-performance sports car is giving way to eco-friendly EVs that accelerate the future of transport	En
BYD is growing fast here cuz oil prices are too expensive	En
Those electric cars are extremely dangerous due to the battery! I would never buy an electric car!	En

3.2. Text Mining

Text mining is an interdisciplinary research field that aims to extract meaningful information from large text data [35]. Text mining, which includes natural language processing (NLP), machine learning, and statistical methods, is a process of extracting insights from unstructured texts [36]. Today, it has a wide range of applications, from social media posts to academic articles, from emails to customer reviews. Especially in the era of big data, text mining has become a critical tool to support informed decision-making [37,38].

Text preprocessing, the first stage of text mining, aims to make the dataset suitable for analysis [39]. This stage consists of several steps to make the text processable and meaningful. First, the text is divided into words or sentences using tokenisation [40]. Then, stopwords such as "and", "with", and "but", which are frequently used depending on the structure of the language but contain low semantic information, are extracted. Another important step is lemmatisation and stemming techniques, whereby words are reduced to their roots to ensure unity of meaning between their affixed forms. Furthermore, the removal of non-essential elements such as punctuation marks, special characters, and numbers contributes to a more accurate processing of the data [41].

Feature extraction aims to convert text data into a numerical format to make them suitable for analysis. In this context, there are several commonly used methods [42]. One of them is the Term Frequency-Inverse Document Frequency (TF-IDF) method, which is used to determine the importance of a word in a given text by evaluating the word inversely proportional to its prevalence in the whole document set [43]. Another method, the Bag of Words (BoW) model, is a representation method based on the frequencies of the words in the text and analyses them without considering the order of the words [44]. Word embeddings, which are among the more advanced meaning capture techniques, enable more in-depth analysis by better representing the semantic relationships of words with techniques such as Word2Vec, GloVe, or FastText [45].

3.3. Sentiment Analysis

Sentiment analysis is a text mining technique used to identify and classify emotional content in texts. This analysis is widely used to understand users' opinions about products, services, political events, or general social issues [46]. Although its main purpose is to determine whether a given text contains positive, negative, or neutral sentiment, in more detailed analyses, different categories of sentiment (e.g., happiness, anger, sadness, fear) can also be evaluated. Nowadays, sentiment analysis has become an important tool for understanding public sentiment, especially in social media, customer feedback, news comments, and forum discussions [47].

Sentiment analysis methods are generally divided into three main categories: rule-based, machine learning-based, and deep learning-based approaches [48]. Rule-based approaches rely on identifying emotional expressions in texts using lexicons and grammatical rules. However, they may fail to understand context and complex elements of language such as irony [49]. Machine learning-based methods, on the other hand, enable the development of models capable of emotion classification using a given training dataset. Algorithms such as support vector machines (SVM), logistic regression, and random forests are examples of this category. In recent years, deep learning models (e.g., long short-term memory (LSTM), convolutional neural networks (CNN), and transformer-based models), especially those that work with large datasets, have become prominent with high accuracy rates in sentiment analysis [50].

3.4. Deep Learning

The LSTM model was selected due to its superior performance in processing sequential data and its ability to capture long-term dependencies in text. Compared to traditional machine learning models, LSTM provides higher accuracy in sentiment classification tasks, particularly in short-text formats like tweets. It is also more effective in handling contextual variations and temporal dependencies, which are essential for understanding opinion trends in social media content.

Sentiment analysis is an important natural language processing (NLP) method used to identify emotional tendencies in text. Although traditional machine learning algorithms produce successful results to a certain extent, deep learning models offer higher accuracy rates when the complexity of text data and contextual relationships need to be considered. In this context, the long short-term memory (LSTM) model is one of the most widely used deep learning architectures in sentiment analysis, especially for its ability to process sequential data [46,51].

LSTM is an improved version of the RNN (recurrent neural networks) architecture. Traditional RNNs are used to make sense of text context by processing past information. However, RNNs are not able to preserve historical information in the long term due to the vanishing gradient problem. LSTM has a special cell structure to solve this problem and can learn long-term dependencies. This feature is a great advantage in tasks where context is important, such as sentiment analysis [52,53].

The main components of LSTM are the following [54]:

- Forget Gate: Determines how much of the previous cell state is kept or forgotten.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

- Input Gate: Determines how much of the existing entrance will be added to the new cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

- Cell Status Update: New information candidate is created by tanh activation.

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_C) \quad (3)$$

- Output Gate: Determines which part of the cell state is output.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) h_t = o_t \cdot \tanh(C_t) \quad (4)$$

In the equations above, x_t is the input vector at time step t; h_{t-1} is the hidden state from the previous step; W_f, W_i, W_o, and W_c are the respective weight matrices; b_f, b_i, b_o, and b_c are the bias terms; and σ denotes the sigmoid activation function.

LSTM models learn the context between words by sequentially processing text in sentiment analysis. This process consists of data preprocessing, model training, and prediction. First, in the data preprocessing stage, the text data are cleaned, tokenisation is applied, stop words are removed, and the text is converted into digital format by word embeddings to make it suitable for the model. Then, in the model training phase, the LSTM model is trained with the labelled dataset to learn sentiment classes such as positive, negative, and neutral. In this phase, the model evaluates contextual relationships between words by learning to capture long-term dependencies in sequential data. Finally, in the prediction and classification phase, when new texts are given to the model, it analyses the context to determine the emotional content of the text and classifies it into the relevant sentiment category. Through this process, LSTM-based sentiment analysis models can detect emotional tendencies in texts with high accuracy [55,56].

The LSTM model used in this study consists of a single-layer bidirectional LSTM with 128 hidden units. A dropout rate of 0.3 was applied after the LSTM layer to prevent

overfitting. The model was trained using the Adam optimiser with a learning rate of 0.001, a batch size of 64, and for 10 epochs. The training–validation split was set at 80/20. Embedding vectors were initialised using pre-trained GloVe embeddings for English and fastText for Turkish. No cross-validation was applied due to the limited size of the Turkish dataset.

3.5. Topic Modelling

In the fields of natural language processing (NLP) and text mining, extracting meaningful structures from large text collections is an important research topic [57]. Topic modelling is a powerful technique for identifying latent topics in ambiguous or unstructured text datasets [58]. It is especially used in large text datasets to understand how certain topics are grouped and which words are associated with which topics. This method can be applied to many different types of texts, from news articles to academic papers, and social media posts to customer reviews [59].

Topic modelling is performed by unsupervised learning methods and analyses texts without predefined tags. In this process, it determines which topics documents can belong to based on word distributions in the text [60]. One of the most widely used topic modelling algorithms is the Latent Dirichlet Allocation (LDA) model [61].

LDA is a probabilistic model developed by Blei, Ng, and Jordan in 2003 and can be used to extract latent topic distributions in texts. LDA assumes that each document can contain multiple topics in certain proportions and that each topic consists of certain words [61].

The LDA (Latent Dirichlet Allocation) model is based on two main assumptions. First, documents are assumed to be composed of topics in certain proportions, i.e., each document contains words belonging to more than one topic, and each topic can have different weights in the document [62]. Second, topics are assumed to be composed of specific words. Each topic is represented by the occurrence of certain words with a certain probability, and these words form a structure that carries a meaning specific to the topic. In this way, the LDA model aims to discover hidden structures in documents and understand the relationship between topics [63].

The basic components of the LDA model are as follows:

- Number of topics (K): This specifies the number of topics that the model will predict.
- Document topics (θ_d): Each document is represented as a mixture of K topics. Here, θ_d is the topic distribution of the d-th document.
- Topic word distributions (ϕ_k): Each topic represents a distribution of words. That is, ϕ_k is the word distribution of the kth topic.
- Word vector ($w_{d,n}$): The words that make up each document. Each word is generated by a topic.

We can express the mathematical structure of the LDA model as follows:

$$p(w, zI\alpha, \beta) = \prod_{d=1}^{D} \left(\prod_{n=1}^{N_d} p\left((w_{d,n} | z_{d,n}, \beta) p(z_{d,n} | \theta_d) \right) \right) p(\theta_d | \alpha) p(\beta | \eta) \quad (5)$$

where

- $w_{d,n}$ is the nth word in the d-th document, and z_d, n is the predicted topic label for this word.
- θ_d represents the topic distribution of the d-th document.
- β and α are the hyperparameters of the Dirichlet distributions.

The number of topics for LDA was determined using the coherence score metric. Multiple iterations were run with topic numbers ranging from 2 to 10, and the model with

three topics yielded the highest coherence score while maintaining semantic interpretability. This approach ensured both statistical validity and practical interpretability of the topic groupings.

3.6. Evaluation

Precision, recall, accuracy, and F1 score are important metrics used to evaluate the performance of the model in classification problems, and each of them analyses the success of the model in different aspects. These metrics allow for a more comprehensive assessment of not only the accuracy of the model but also its errors and shortcomings [64].

Accuracy shows how accurately the model predicts across all data, that is, the ratio of correct predictions to total predictions [65].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{6}$$

Precision indicates how many of the samples that the model predicts as positive are positive, that is, the accuracy of the model's predictions to the positive class [65].

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{7}$$

Recall indicates how many of the truly positive examples the model correctly predicts, that is, how well it captures the entire positive class [66].

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{8}$$

The F1 score is the harmonic mean of precision and recall. This metric attempts to balance both the rate of correct positive predictions (precision) and the rate at which the positive class is correctly identified (recall). In particular, it is used when a trade-off between precision and recall is desired [66,67].

$$\text{F1} = \frac{2 * \text{Recall} * \text{Precision}}{\text{Precision} + \text{Recall}} \tag{9}$$

During model training, hyperparameter optimisation was performed manually by evaluating different configurations of learning rate, batch size, and number of epochs to maximise model performance. The training and testing sets were split using an 80/20 ratio. Standard evaluation metrics including precision, recall, accuracy, and F1 score were used to assess the model's classification performance. These metrics provided a comprehensive understanding of the model's ability to distinguish between sentiment categories.

4. Results

Table 2 shows the classification performance of Turkish and English tweets about EVs using the deep learning-based LSTM model. The success metrics of the model are evaluated in terms of precision, recall, accuracy, and F1 score, and high accuracy is achieved in both languages.

Table 2. Performance measurement.

Metrics	English Tweet	Turkish Tweet
Precision	0.932	0.972
Recall	0.953	0.981
Accuracy	0.921	0.967
F Score (F1)	0.942	0.977

Table 2 shows the classification success of Turkish and English tweets about EVs using the deep learning-based LSTM model. Looking at the precision values, most of the positive predictions of the model were correct in both languages, with 97.2% success for Turkish tweets and 93.2% success for English tweets. Recall values are also quite high, reaching 98.1% for Turkish tweets and 95.3% for English tweets, indicating that the model can largely accurately capture the positive class. Accuracy results show an accuracy of 96.7% for Turkish tweets and 92.1% for English tweets, indicating that the overall performance of the model is successful. The F1 score balances both precision and recall performance of the model, reaching high values of 97.7% for Turkish tweets and 94.2% for English tweets. These results show that the model provides high accuracy, precision, and sensitivity in both languages and thus can effectively classify tweets about EVs.

Figure 1 shows the categorisation of tweets according to sentiment.

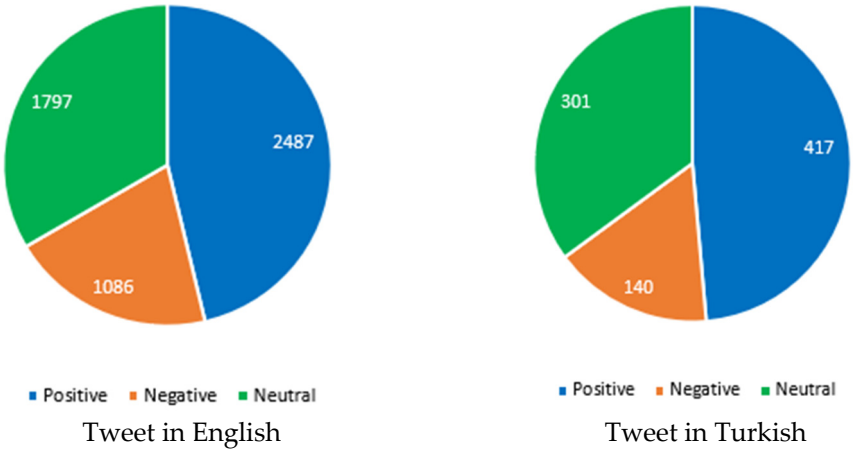


Figure 1. Emotion analysis.

The results of the sentiment analysis of Turkish and English tweets about EVs using deep learning-based models are shown in Figure 1: 46.8% of Turkish tweets were positive, 15.7% were negative, and 37.5% were neutral. In English tweets, a 51.8% positive, 22.6% negative, and 25.6% neutral sentiment distribution was determined. This sentiment distribution shows that the general perception towards EVs is predominantly positive in both languages. The slightly higher proportion of positive tweets in English (51.8%) may suggest that there is more widespread acceptance and support for EVs globally. On the other hand, the relatively high percentage of negative posts in English tweets (22.6%) suggests that some concerns or criticisms in this area are also noteworthy. The higher proportion of neutral tweets (37.5%) in Turkish tweets may indicate that there is more neutral commentary or information sharing on the topic and that users refrain from expressing a definite positive or negative opinion. In general, although the positive perception of EVs is strong in both languages, the presence of negative sentiment rates indicates that factors such as price, lack of infrastructure, range anxiety, or battery life are still a matter of debate. The higher rate of negative sentiment, especially in English posts, suggests that there is more debate and criticism in the global market, while the relatively high rate of neutral sentiment in Turkish posts may suggest that EVs are not yet widespread enough in Turkey and that people are trying to learn more about the subject.

Word frequency analysis is an important method to identify consumers' perceptions of EVs and topics of discussion [68]. Within the scope of this analysis, the most frequently used words in positive, negative, and neutral contexts were analysed, and meaningful inferences were drawn about how consumers evaluate EVs. Table 3 shows the most frequently used words in English tweets, and Table 4 shows the most frequently used words in Turkish tweets.

Table 3. Frequency list of English tweets.

Positive	Negative	Neutral
Price	Charge time	Bill
Use	Charging	Need
Money	Battery	Time
Market	Gas	Gas
Green	Range	Model

Table 4. Frequency list of Turkish tweets.

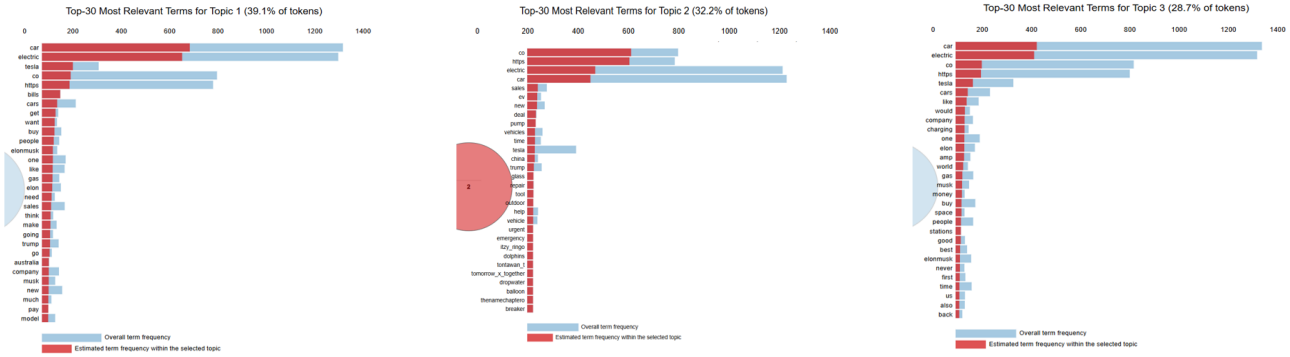
Positive	Negative	Neutral
Produce	Charging	Production
Company	Battery	Sales
Use	Range	Motor
Engine	Company	Market
Model	Price	Infrastructure

The text mining analysis on EVs provides important clues in determining consumers' perceptions of these vehicles. The words "price", "use", "use", "money", "market", and "green" that are most frequently mentioned in a positive context indicate that EVs stand out for their economic advantages and environmental benefits. The positive perception of the word "price" suggests that accessibility has increased due to cost competitiveness or incentives. The frequent use of the word "use" indicates that these vehicles are practical in daily life, while the words "money" and "market" reveal that consumers are interested in the growth of the sector and investment opportunities. Furthermore, the prominence of the word "green" indicates that environmental sustainability is an important criterion. In a negative context, the words "charge time", "charging", "battery", "gas", and "range" are most frequently mentioned, reflecting consumers' main areas of concern. Long charging times and inadequate infrastructure, battery life, and range concerns stand out as the biggest factors limiting users' transition to EVs. In the neutral category, words such as "bill", "need", "time", and "model" reflect discussions on daily usage costs, consumer expectations, and model comparisons. While the word "bill" includes assessments of energy consumption costs, the word "need" refers to consumers' need and expectations for EVs. Overall, while consumers appreciate the economic and environmental benefits of EVs, issues such as strengthening charging infrastructure, improving battery performance, and solving range issues stand out as critical areas to accelerate adoption.

The analysis of Turkish tweets reveals both positive and negative aspects of the perception of EVs. In the positive context, the words "produce", "company", "use", "engine", and "model" appear most frequently, indicating that consumers have positive views of electric vehicle production, ease of use, and engine technologies. The prominence of the words "produce" and "company" in particular reveals that the automotive sector's investments in this field are followed with interest and there is an expectation for the expansion of production capacity. On the other hand, the negative words "charging", "battery", "range", "company", and "price" point to the main factors preventing the widespread use of EVs. While the length of charging times, battery life, and range concerns are among the most frequently cited concerns of consumers, the association of the word "price" with negative comments suggests that high costs slow down the adoption process. In addition, the word "company" indicates that the services offered by some companies

are criticized, suggesting that differences between brands are important in terms of user experience. The words "production", "sales", "motor", "market", and "infrastructure" in the neutral context reflect general discussions on the production and sales processes, motor technologies, and charging infrastructure of the electric vehicle sector. The word "infrastructure" is in the neutral category, indicating that charging stations and general infrastructure are evaluated both positively and negatively. Overall, Turkish tweets reveal a positive perception of EVs in terms of production, usage, and environmental benefits, but technical and economic barriers such as charging infrastructure, battery life, range, and high cost are seen as important factors for consumers in the diffusion process. These results suggest that there is a need to increase incentives to reduce costs, improve battery and charging technologies, and strengthen infrastructure to support the growth of the sector.

Topic modelling is a text mining method used to identify latent themes in large-scale text data. Models such as Latent Dirichlet Allocation (LDA) group texts around specific topics by analysing word distributions [61]. The reason for identifying three topics in the study is to show that tweets about EVs are divided into different themes in terms of content. The number of topics was determined by considering the consistency of the models, topic decomposition, and the structure of the dataset, and this choice allows for meaningful categorisation of the texts. Figure 2 shows the topic modelling generated from English tweets.



(**a**) (**b**) (**c**)

Figure 2. LDA terms (English tweets) (**a**) Topic 1 (**b**) Topic 2 (**c**) Topic 3.

Topic 1: Reasons for Preference of EVs and Purchasing Trends

This topic addresses how EVs are perceived by consumers and the factors that influence their purchasing decisions. Users' interest in specific brands, cost considerations, and desire to own are among the most prominent factors. The advantages offered by EVs, long-term savings opportunities, and environmental contributions are among the reasons for their preference.

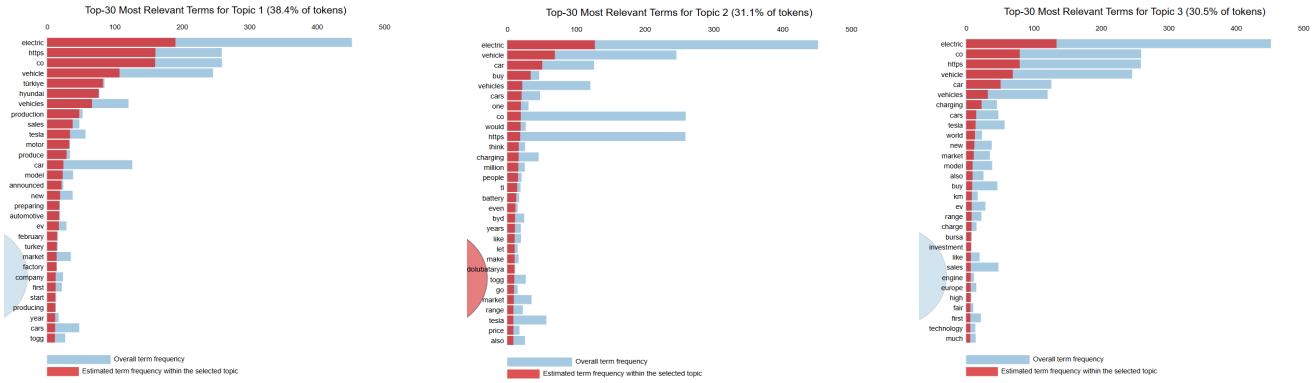
Topic 2: The Role of Brands and Companies in the Electric Vehicle Market

This topic focuses on the position of large companies operating in the automotive sector in the electric vehicle market. Consumers discuss the innovation processes and the models offered by companies in the sector. The development of EVs, brand image, and investments in technology also play an important role in this context.

Topic 3: Current Developments in the Electric Vehicle Market and Sales Strategies

This topic includes assessments of recent innovations in the sector, marketing strategies, and sales performance. New model introductions, pricing policies, and incentives are important factors shaping consumer perceptions of EVs. Moreover, the expansion of the sector and the increase in competition cause consumers to follow the market more closely.

Figure 3 shows the topic modelling generated from Turkish tweets.



(**a**) (**b**) (**c**)

Figure 3. LDA terms (Turkish tweets). (**a**) Topic 1 (**b**) Topic 2 (**c**) Topic 3.

Topic 1: Electric Vehicle Production and Market Development

This topic focuses on the production and sales of EVs and the position of brands in the sector. In particular, the production processes and market dynamics of companies operating in the automotive sector come to the fore. Turkey's investments in electric vehicle production and the impact of certain automobile brands on the market have an important place in this context. In addition, growth trends and competition in the sector are among the key topics of interest to consumers.

Topic 2: General Perception of EVs and Charging Infrastructure

This topic includes discussions on the widespread use of EVs and infrastructure. Consumers evaluate the role of these vehicles in daily life and the adequacy of charging stations. While the advantages and ease of use of EVs are emphasized, issues such as charging times and the accessibility of charging stations are also raised.

Topic 3: Electric Vehicle Purchasing Trends and Preferences

This topic focuses on consumers' motivations and decision-making processes for purchasing EVs. While evaluating the advantages of these vehicles, users make comparisons of the models and features they prefer. Price, performance, and daily use requirements are among the determining factors in a consumer's choice of vehicle.

These identified topics provide deeper insights into the key issues that shape consumer sentiment toward EVs. For example, the prominence of themes like charging infrastructure and company-related perceptions suggests that users are not only concerned with technical specifications but also with broader institutional factors. In Turkish tweets, discussions around domestic production and infrastructure needs reflect national concerns about industrial capacity and accessibility. In English tweets, the focus on market trends and brand competition points to a more globalised consumer perspective.

5. Discussion

The analysis of the social acceptance of EVs in this study shows significant similarities and differences when compared to the existing literature. This examination using social media data reveals the various factors affecting the acceptance of EVs in a more dynamic way. In the literature, the factors determining the acceptance of EVs are generally based on factors such as technological acceptance, driving experience, and environmental impacts [14,69]. In this study, social media posts show how these factors are shaped in the perceptions of social media users and how these perceptions affect social acceptance.

Technological acceptance stands out as a determining factor in the social acceptance of EVs. A study by Burkert et al. (2021) states that inadequate charging infrastructure and low battery capacity are the main factors preventing users from adopting EVs [17]. A similar finding was identified in this study. In English tweets, users expressed their concerns

about the limited range and charging infrastructure of EVs. In Turkish tweets, on the other hand, while such concerns were less common, positive features such as environmental friendliness were emphasised more. This difference reveals how users' perceptions of EVs in certain geographical regions are shaped by technological barriers. The dominance of range anxiety and charging concerns in both languages can be linked to the current state of infrastructure development. In Turkey, although the EV market is growing, infrastructure is still limited, leading to neutral or cautious sentiments. In global markets, where EVs are more common, user expectations are higher, and criticisms are more pointed. These differences may also be influenced by recent policies such as tax incentives in Europe or TOGG's launch in Turkey, both of which influence consumer discussion.

The influence of social norms and collective influence on the acceptance of EVs is another important finding. Barth et al. (2016) reported that social norms and collective influence play an important role in the acceptance of EVs [69]. In this study, it was found that users' perceptions of EVs are largely shaped by collective values such as environmental awareness and social responsibility. In Turkish tweets, positive perceptions of environmentally friendly vehicles and belief in their social benefits are more evident. In English tweets, these positive perceptions were generally associated with environmental concerns and sustainability themes. This finding suggests that the acceptance of EVs is shaped not only by individual benefits but also by social responsibility.

In addition, the relationship between the acceptance of EVs and the political ideologies of individuals is also frequently emphasised in the literature. Ramachandaramurthy et al. (2023) stated that social perceptions of EVs are influenced by individuals' political views [70]. In this study, it was observed that users' positive or negative perceptions of EVs in Turkish and English tweets were shaped by political views and social ideologies. Especially in English tweets, it was found that the comments made about EVs generally overlapped with individuals' environmental awareness and political views.

The relationship between EVs and sustainability goals is another important topic of debate. Omahne et al. (2021) stated that the social acceptance of EVs is largely linked to public awareness of their environmental friendliness and sustainability goals [21]. In this study, in Turkish tweets, users strongly emphasised the contribution of EVs to the environment and perceived them as important for sustainability. In English tweets, on the other hand, it was observed that these perceptions were more associated with social responsibility and environmental policies. This is a finding that shows that the acceptance of EVs is shaped not only by technological factors but also by environmental and sustainability goals.

Finally, the role of social media platforms in shaping public perceptions about EVs was also an important finding. Wang et al. (2018) emphasise the impact of social media in influencing public perceptions and forming public opinion [71]. In this study, posts on the social media platform X rapidly spread and shaped social perceptions on the acceptance of EVs. Social media has become a platform that influences the social acceptance of EVs by organising users' perceptions according to social norms.

This study makes valuable contributions to the literature analysing the social acceptance of EVs. The analysis of users' comments on social media reveals that various factors such as environmental concerns, technological barriers, social norms, and political views shape the acceptance of EVs. The findings suggest that the acceptance of EVs is based not only on individual preferences but also on social and cultural factors. The originality of the study lies in the use of social media data as an effective source to dynamically analyse social perceptions. In future studies, a more detailed examination of the views of users in different geographical regions on EVs will contribute more to the literature in this field.

The higher proportion of neutral tweets in the Turkish dataset may reflect the relatively nascent stage of EV adoption in Turkey. According to reports by Turkey's Ministry of Energy

and Natural Resources, public charging infrastructure is still developing, and government incentives are more limited compared to the EU or US. Moreover, national consumer surveys indicate a lack of firsthand experience with EVs, which may explain the prevalence of observational or neutral commentary rather than strong opinions. In contrast, English tweets—often from markets with higher EV penetration—show more polarised views due to direct user experience and policy engagement.

The findings provide actionable insights for EV manufacturers and policymakers. For instance, improving public communication strategies and responding directly to social media concerns may help build trust. Marketers could emphasise economic and environmental benefits more strongly in regions where neutral sentiment is high. Policymakers can use social media signals to identify infrastructure gaps and prioritise investments in charging stations.

One limitation of this study is the imbalance between the English and Turkish datasets. The relatively small number of Turkish tweets may not fully capture the diversity of public opinion in Turkey, potentially leading to higher variance and reduced generalisability. While oversampling techniques were considered, we prioritised using authentic, non-augmented data to maintain the natural distribution of user sentiments. Future research should aim to expand the Turkish dataset to ensure more robust cross-linguistic comparisons.

6. Conclusions

In this study, sentiment analysis and text mining techniques were used on Turkish and English tweet data to understand the social acceptance of EVs, consumers' electric vehicle purchasing behaviours, and consumer perception and acceptance processes about EVs. The data collected through the social media platform X reflect the social perception of EVs and play an important role in determining the factors that shape this perception. The findings show that EVs are generally welcomed positively, but there are also some concerns. For instance, sentiment analysis revealed a higher share of neutral tweets in Turkish data and more negative tweets in English data, reflecting differing stages of public awareness and infrastructure readiness. Topic modelling identified key concerns, including charging infrastructure, battery life, cost, and brand perception, all of which shape social acceptance.

The analysis of the general sentiment about EVs revealed that positive comments were more common in both Turkish and English tweets. However, more neutral sentiments were found in Turkish tweets, suggesting that users have a neutral and objective attitude towards learning more about EVs. In English-language tweets, negative comments are more common, indicating that concerns and challenges about EVs are being expressed more globally. This result suggests that some global factors affecting the acceptance of EVs, especially economic and technical barriers, constitute obstacles to their widespread adoption in society.

The findings on the social acceptance of EVs show that environmental benefits are emphasised in a positive way. Users appreciate the environmentally friendly features of EVs, stating that they reduce dependence on fossil fuels and cause less damage to the environment. However, some important concerns limiting the acceptance of EVs have also come to the fore. Technical and economic concerns such as battery life, charging infrastructure and vehicle prices were more frequently mentioned, especially in English tweets. This reflects users' concerns about the high economic costs and limited range of EVs. Furthermore, the lack of widespread availability of charging stations and long charging times for batteries are also among the factors hindering the wider acceptance of these vehicles. Although Turkish and English tweets expressed similar concerns about these issues, cultural differences were also observed. While Turkish tweets are characterised by more neutral language and neutral comments, English tweets show more negative emotions

and concerns. This reveals the differences in the approach of both societies towards EVs and the cultural factors affecting the acceptance of these vehicles.

This study presents important findings on the social acceptance of EVs by comparing Turkish and English social media data. Although there are similar studies in the literature, this study offers a new perspective on how social perception is shaped by language and culture by comparing social media data in different languages. In addition, environmental concerns and technical barriers, which have frequently been emphasised in previous studies on the social acceptance of EVs, are discussed in more detail in this study, and the differences between Turkish and English tweets are revealed. This contributes to a better understanding of public perceptions of EVs.

The findings obtained in this study are of particular importance in terms of understanding the factors affecting the consumer decision-making process for EVs. These findings significantly overlap with previous research in the literature. The results of sentiment analysis and topic modelling on social media show that consumers' perceptions of EVs are significantly affected by factors such as economic advantages, environmental concerns, range anxiety, and charging infrastructure. The findings of the study are in line with the results of Noel et al. (2019), who reported that range anxiety and inadequate charging infrastructure negatively affect consumer decisions [72]. Similarly, Rezvani et al. (2018) found that economic advantages, social norms, and individual satisfaction shape consumers' electric vehicle preferences [73]. In this study, it was observed that economic incentives and environmental concerns play an important role in consumer perceptions. As suggested by Jansson et al. (2017), the influence of the social environment on EV adoption is further confirmed by social media interactions and user comments [74]. However, a distinctive feature of this study is its novel contribution to the literature in terms of providing a new perspective on consumer trends and real-time perception changes.

The findings of this study provide an important basis for understanding the factors affecting the social acceptance of EVs. Future studies could examine in more detail the impact of steps such as strengthening charging infrastructure, improving battery technologies, and lowering prices on increasing the adoption of EVs by a wider range of users. Furthermore, it is important to collect and analyse more data to understand users' behaviour towards learning more about EVs.

This study has limitations. The dataset is limited to one month of tweets, which may not capture long-term trends. Additionally, there may be bias due to the platform demographics, with younger and more tech-orientated users being over-represented. Language-specific preprocessing and model accuracy could also affect comparability across Turkish and English tweets.

In the study, the collection of social media data in a limited time has narrowed the scope of the research. In future studies, broader and more comprehensive analyses of the social acceptance of EVs can be conducted with data collected in different geographies and over a longer period. In such studies, not only sentiment analyses but also an in-depth examination of the specific questions, demands, and concerns of users can be conducted.

Future research could benefit from combining social media data with survey or interview data for triangulation. Additionally, exploring deep learning models like BERT or transformer-based architectures could enhance sentiment detection, especially in multilingual contexts. Extending the study period or including other social platforms like Reddit or Instagram would also offer a broader picture of public discourse.

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