PressAcademia
www.pressacademia.org/journals/rjbm
RJBM
ISSN 2148-6689
Research Journal of Business and Management YEAR 2024 VOLUME 11 ISSUE 2

CREATING A COMPREHENSIVE DATA SET FOR DECEPTION DETECTION STUDIES IN TURKISH TEXTS

DOI: 10.17261/Pressacademia.2024.1960
RJBM- V.11-ISS.2-2024(7)-

Ekin Akkol[1], Yilmaz Goksen[2]
[1]Izmir Bakircay University, Izmir, Turkiye.
ekin.akkol@bakircay.edu.tr , ORCID: 0000-0003-2924-8758
[2]Dokuz Eylul University, Izmir, Turkiye.
yilmaz.goksen@deu.edu.tr , ORCID: 0000-0002-2291-2946

Date Received: November 1, 2024 **Date Accepted:** December 20, 2024

To cite this document
Akkol, E., Goksen, Y. (2024). Creating a comprehensive data set for deception detection studies In Turkish texts. Research Journal of Business and Management (RJBM), 11(2),
Permanent link to this document: http://doi.org/10.17261/Pressacademia.2024.1960

ABSTRACT

Purpose- Deception detection has gained increasing importance with the widespread use of digital communication and online platforms. While numerous studies have been conducted on deception detection in various languages, a significant gap remains in the availability of a Turkish-language dataset for detecting deceptive reviews. This study addresses this gap by creating a comprehensive dataset specifically for deception detection in Turkish hotel reviews, including real, fake, and AI-generated comments. The dataset aims to facilitate research on deception detection, enhance the reliability of user-generated content, and contribute to the development of automated methods for identifying deceptive texts.

Methodology- The study included a dataset of 5,013 Turkish hotel reviews, including real reviews from Tripadvisor, fake reviews generated by humans, and fake reviews generated by AI using the OpenAI GPT API. The collected dataset underwent extensive preprocessing to ensure quality and reliability, including data cleaning, filtering criteria, and balancing the distribution of real and fake comments. Descriptive and statistical analyses were performed to identify linguistic patterns and structural differences across these three categories. Specifically, linguistic features such as comment length, complexity, readability (measured using the Gunning Fog Index), and pronoun usage were examined.

Findings- Real comments are longer and more detailed than fake and AI-generated comments, while fake comments are simpler and clearer, which supports deception detection studies in other languages. AI-generated comments frequently use the pronoun 'we', while fake comments tend to mimic personal experience with the pronoun 'I'. In addition, the pronoun usage in real comments is more balanced and shows an authentic language structure.

Conclusion- This study makes important contributions for fake comment detection by providing the first large-scale Turkish deception detection dataset. The findings can help businesses improve the credibility of online comments. Future work could focus on machine learning applications and comparisons with different languages.

Keywords: Deception detection, Turkish dataset, text analysis, fake reviews, hotel reviews
JEL Codes: C80, M10, D83

1. INTRODUCTION

Deception is defined as the act of deliberately instilling in another individual a belief that the individual knows to be false (Ekman & O'Sullivan, 1991; Vrij et al., 2008). People admit that they are deceptive in 27% of face-to-face interactions, 21% of instant messaging, 37% of phone calls and 14% of e-mail communications (Hancock et al., 2004). As communication technologies become more prevalent in our daily interactions, the act of deception becomes easier and more common. Although deceptions are often not seen as a significant problem, some of them can lead to consequences that cannot be ignored (Viji D. & Gupta, 2022). Nowadays, as the use of the Internet increases, deceptions can harm individuals, businesses, communities, governments and public institutions both financially and emotionally. Thanks to its anonymity and accessibility, the Internet enables deceptive behaviors to be carried out more widely and effectively. Acts such as identity theft, cyberbullying, fraud and creating fake comments over the Internet can cause both money loss and psychological trauma (Patchin & Hinduja, 2010; Whitty & Buchanan, 2012). These actions not only harm people, but can also cause serious damage to businesses, such as financial losses, reputational damage and decreased customer confidence.

Internet-based deception and fraud particularly target financial institutions, e-commerce platforms, service sector companies, technology companies and small businesses. Disinformation and misinformation spread over the Internet can polarize society and undermine general trust. Especially nowadays, when digital communication is widespread, detecting deceptions in language has become a part of strategic management processes. Strategic management involves long-term planning and decision-making processes to achieve the goals of organizations (Esmaeili, 2015). In this context, the dissemination of fake information and comments may lead to the development of misguided strategies and inefficient use of business resources. Especially customer feedback and public comments provide important data in shaping the strategic plans of organizations. However, when the accuracy of these data is not ensured, businesses may make wrong decisions and their efforts to increase customer satisfaction or gain competitive advantage may be hampered. Effective management of strategic issues such as customer satisfaction, reputation management and public perception plays an important role in helping businesses adapt to changing market conditions and remain resilient to crisis situations.

Natural language processing techniques have been widely used in deception detection studies in recent years. The most important constraint in deception detection studies is the collection of the required data. In order to detect the significant differences between deceptive and real texts, a sufficient number and quality of data is needed. Since deception detection is a very difficult and critical issue for humans, it is also difficult to collect real-life data. In the literature, many data sets have been created to be used in deception detection studies. Some of the data sets are summarized in Table 1.

Table 1: Data Sets Used in Deception Detection

Reference	Data Source	Content Type	Number of Comments	Data Set Language
Salminen, 2024	Amazon and GPT-2	Product Reviews	20000 Real 20000 Fake	English
Ott et al., 2011	Tripadvisor and Mechanical Turk	Positive Hotel Reviews	400 Real 400 Fake	English
Ott et al., 2013	Expedia, Hotels.com, Orbitz, Priceline, TripAdvisor, Yelp and Mechanical Turk	Negative Hotel Reviews	400 Real 400 Fake	English
Mukherjee et al., 2013	Yelp	Restaurant and Hotel Reviews	55025 Real 9170 Fake	English
Ignat et al., 2024	Booking	Hotel Reviews	10000 Real 10000 Fake	Turkish, Chinese, English, French, German, Italian, Korean, Romanian, Russian, Spanish
Catelli et al., 2023	TripAdvisor and Mechanical Turk	Tourist Attractions in Naples	400 Real 400 Fake	Italian
Liv d., 2014	Dianping	Restaurant Reviews	6241 Real 5957 Fake	Chinese
Hammad and El-Halees, 2013	TripAdvisor, Booking, Agoda	Hotel Reviews	2469 Real 379 Fake	Arabic
Van Dinh et al., 2022	E-commerce platforms in Vietnam	Product Reviews	14609 Real 5261 Fake	Vietnamese

As shown in Table 1, although there are datasets in languages such as English, Chinese, Arabic, Italian and Spanish there is no dataset prepared in Turkish language for deception detection in reviews about hotels, restaurants, products and locations. There are some studies that include Turkish-language comments in the dataset, but the data source in these studies is artificial intelligence, not humans. Turkish is one of the languages where artificial intelligence is most unsuccessful in generating fake comments (Ignat et al., 2024).

The main purpose of this study is to create a reliable data set for text-based deception detection studies in Turkish as well as in other languages. This study aims to increase the information reliability of strategic management processes by focusing on the detection of deception in Turkish texts and provides an important data set in this context. The study seeks to answer the following main research question: "In the context of Turkish hotel reviews, what linguistic and structural differences are observed between real, fake and AI-generated texts?" In the research process, quantitative approaches were used, focusing on how people say their reviews rather than what they say. In this context, various statistical analyses were performed on the generated data set. Linguistic features of the texts such as length, complexity and pronoun usage were quantitatively evaluated. Descriptive statistics and quantitative analysis models such as Gunning Fog Index were used in these analyses. Considering the methods used in the studies in the literature, a dataset of 5013 hotel reviews was created, including data from three different sources: real, fake and AI-generated.

This article consists of four main sections. First, the Introduction section discusses the purpose of the study, the gap in the literature, and the approach proposed to fill this gap. The second section explains the process of creating the dataset in detail, and touches on data sources, selection criteria, and data cleaning stages. The third section presents the descriptive analyses performed on the dataset, and details grammatical and structural differences. Finally, the fourth section discusses the results of the study, evaluates the contribution of the findings to the literature, and suggests future research.

2. METHODOLOGY

In order to prepare the dataset consisting of fake and real hotel reviews in Turkish, the methods followed in the "Deceptive Opinion Spam Corpus v1.4" dataset created by Ott et al. (2011, 2013), which is highly accepted in the literature and used as a reference for the preparation of many other datasets, were taken into consideration. The data collection methods in this study were not limited to the data collection methods in this study, and a data set was created by considering the different characteristics of Turkish and various expert comments. It was decided that the dataset would consist of hotel data, and in this direction, firstly, the region with the highest number of hotel reviews in Turkish was investigated. As a result of the research, the region with the highest number of hotel reviews in Turkey was determined as the Mediterranean region. Afterwards, hotels were filtered on the Tripadvisor platform as the Mediterranean region and 20 hotels with the highest number of reviews were selected. The Tripadvisor platform is open to everyone, and anyone can comment on it, and even if users sign agreements that they will not make fake reviews while registering, it is not provable that the comments published on these platforms are real comments with a hundred percent rate. Therefore, in order to increase the reliability of the dataset, a set of criteria was determined and data that did not meet these criteria were not included in the dataset.

2.1. Real Reviews Dataset

The raw data set obtained from Tripadvisor consists of 36559 reviews of 20 hotels. There are 2000 columns in the dataset, i.e. 2000 features belonging to each review. However, since not all of these features can be used in deception detection, the dataset was first simplified by selecting only the columns to be used. The current dataset includes the parameters "hotel name", "user comment", "number of times the user's comment was found useful", "number of comments the user has made so far" and "whether the user has a photo in the comment". The dataset containing real user reviews is divided into two as "Positive Real Hotel Reviews" and "Negative Real Hotel Reviews" as they will be filtered according to different criteria to increase the reliability of the data. For the dataset with positive reviews, the reviews of users who gave 4 and 5 points to the hotels were used, while for the dataset with negative reviews, the reviews of users who gave 1 and 2 points to the hotels were used.

In order to ensure that the positive hotel reviews consist of the most reliable reviews, firstly, the reviews of users with a maximum of 50 reviews and a minimum of 3 reviews were filtered. When the data set was analyzed, it was considered that some users had thousands of different hotel reviews and that these users' reviews could be fake for advertising purposes, etc. Therefore, the reviews of users with more than 50 reviews were not included in the data set. Likewise, considering the possibility of users who make 1 or 2 reviews and do not actively use the platform to fake a single hotel, the comments of these users were excluded from the dataset, as in the studies in the literature. Since it is thought to be more likely that users who add photos from the hotel to their reviews are people who have stayed at the hotel, the comments of users who commented with photos were prioritized while creating the dataset, considering other criteria. Repeated comments in the dataset were also removed as they were likely to be fake. In addition to all these, interviews were made with an authorized person who owns chain hotels in the Mediterranean region and it was learned that people such as managers, front office staff, animators, bartenders in hotels have duties to encourage customers to write fake comments in various ways and it was decided that these comments should be removed in order to increase the reliability of the dataset. Accordingly, comments containing the words "sir" and "madam" as well as some proper nouns were removed from the positive hotel reviews dataset.

For the negative reviews to consist of the comments with the highest reliability, the comments of users with a maximum of 50 and a minimum of 3 comments were taken and comments with photographs were prioritized. In addition, considering that it is a criterion that strengthens reliability for negative comments, the criterion that the comment is found useful by other users at least 2 times was taken into consideration. Comments that were not supported by other users at least 2 times as useful were removed from the data set. In addition, as in the positive data set, repetitive comments were removed.

2.2. Fake Reviews Dataset

In addition to the real comments, a fake comments dataset was also created to perform deception detection studies. There are two options for creating such a dataset. The first option is to generate fake reviews using artificial intelligence, and the second option is to ask people who have never visited the hotels to generate fake reviews about the hotels. In this study, data was generated by both methods. OpenAI GPT API was used to generate data with artificial intelligence. For real people to generate fake reviews, a Google Form was created with links to 20 hotels. People who volunteered to fill out the form were divided into two groups and one group was asked to make negative comments and the other group was asked to make positive comments. In order to avoid repetitive comments and to keep the data quality at a high level, each person was asked to make only one comment for a hotel. People were asked to examine the hotels and make comments specific to the hotels, to avoid short comments as much as possible, to use only Turkish language in their comments, and to make completely original, non-copy-paste comments. In addition, the number of previous stays of the reviewers in a hotel was also questioned in the prepared form and the assumption was made that the reviews of people with more experience of staying in more hotels would be more reliable. Examples of the fake reviews' dataset obtained from individuals are presented in Table 2.

Table 2: Fake Hotel Reviews Dataset

Number of previous hotel vacations	Fake Hotel Reviews	Fake Hotel Reviews (Translated)
4-6 times	Otel görevlileri çok kabaydı ve hiç yardımcı olmadı. Kaldığımız 7 günlük otel planlamasının 4 gününde wi-fi sorunları mevcuttu ve teknik ekip bir türlü yardımcı olmuyordu. Ayrıca, otel plajı çok pisti sanırım bir daha buraya gelmeyeceğim.	Hotel staff were very rude and not helpful at all. There were wi-fi problems on 4 days of the 7-day hotel plan and the technical team could not help us. Also, the hotel beach was very dirty, and I think I will not come here again.
More	Belekte bir otele göre berbat. Golf sahası desem golf sahası değil halı saha desem halı saha değil cidden berbattı. Aynı zamanda aktivite yapmak için gelmiştik ama tamamı ile bir hayal kırıklığıydı. Verdiğimiz paraya asla değmedi.	Terrible for a hotel in Belek. If I say golf course, it's not a golf course, if I say astroturf, it's not an astroturf, it was really awful. At the same time, we came to do activities, but it was a complete disappointment. It was never worth the money we gave.
1-3 times	Geçen yaz arkadaşlarımla tatil için planladığımız bir oteldi ancak keşke hiç gitmemiş olsaydık. Temizlik, personel ilgisi, hijyen her şey o kadar vasat ve kötüydü ki gittiğimize çok pişman olduk. Keşke bu denli gösterişli tanıtımlar yapmak yerine biraz hijyene önem verilseydi. Odamızdaki çarşaflarda gözle görülür lekeler vardı, plajlar çöple doluydu. Bizim için çok kötü bir tecrübeydi ve kimseye tavsiye etmiyorum.	It was a hotel we planned for a holiday with my friends last summer, but I wish we had never been there. Cleanliness, staff interest, hygiene, everything was so mediocre and bad that we regretted going. I wish a little hygiene was given importance instead of making such flashy promotions. There were visible stains on the sheets in our room, the beaches were full of rubbish. It was a very bad experience for us, and I do not recommend it to anyone.
1-3 times	Balayı için tercih etmiştim. Berbat bir deneyimdi. Ücretsiz verilecek olan kahvaltıdaki ürünler bozuktu. Vadedilen ücretsiz fotoğraf kalitesi de çok kötüydü. Rakip çekebilmek adına bu tarz hinlikler yapmaya gerek var mıydı bilemiyorum. Hiç memnun kalmadım.	I preferred it for honeymoon. It was a terrible experience. The products in the free breakfast were broken. The promised free photo quality was also very bad. I don't know if there was a need to do such tricks in order to attract competitors. I was not satisfied at all.
4-6 times	Golf alanında randevu sistemiyle çalışıldığı belirtilmişti ancak randevu saatimizde alana gittiğimizde farklı bir gruba da aynı saate randevu verildiğini fark ettik ve epey kargaşa yaşadık. Ne bizim ne de diğer müşterilerin bu şekilde mağdur edilmesi kabul edilebilir bir şey değil. Bir daha gelmeyi düşünmüyorum.	It was stated that the golf area was working with an appointment system, but when we went to the area at our appointment time, we realised that a different group was given an appointment at the same time, and we had a lot of confusion. It is not acceptable that neither we are nor other customers are victimised in this way. I do not plan to come again.

Fake hotel reviews created by individuals were checked for compliance with the specified criteria, and comments that did not meet the criteria were removed from the dataset. In its final form, the dataset consists of a total of 1671 fake hotel reviews, 933 of which are positive and 738 of which are negative. In order to be balanced with the fake hotel reviews dataset, the same number of data was generated by artificial intelligence, and the final dataset was created by taking the same amount of data from the real hotel reviews dataset as the number of reviews in the fake dataset. Numerical information about the dataset is shown in Table 3.

Table 3: Number of Comments in the Data Set

Data Source	Number of Positive Comments	Number of Negative Comments
TripAdvisor	933	738
Google Forms	933	738
Artificial Intelligence	933	738

3. ANALYSIS AND FINDINGS

Many descriptive analyses are conducted on the data sets for detecting deception in the literature. The main purpose of these descriptive analyses is to identify patterns in the data sets and to investigate whether general judgments can be reached. In most of the studies, it has been found that deceptive interpretations are much more general, summarized and less detailed (Markowitz and Hancock, 2014; Louwerse et al., 2010; Ott et al., 2011; Xu et al., 2015). Based on these inferences in the literature, the length analysis of the comments in the data set was performed. The results of the analysis are shown in Table 4.

Table 4: Length of Comments in the Data Set

	Average Comment Length (Characters)	Shortest Comment Length (Characters)	Longest Comment Length (Characters)
Real Reviews	707.97	51	6226
Fake Reviews	216.44	9	1391
AI Generated Fake Reviews	103.35	73	145

When the lengths of the comments were analyzed, it was found that the real comments were much longer than the fake and artificial intelligence generated fake comments. In other words, the real comments in the generated dataset are much more detailed and detailed than the fake comments. This coincides with most of the studies in the literature and reveals that the amount of detail may have a meaning on the authenticity of the comments according to the Turkish data set. In addition to this, a cognitive load analysis was also conducted by focusing on how much mental effort is required to understand the texts. Gunning Fog Index was used for this analysis. Figure 1 expresses the Gunning Fog Index equation.

Figure 1: Gunning Fog Index

$$0.4\left(\left(\frac{Total\ Number\ of\ Words}{Total\ Number\ of\ Sentences}\right)+100\left(\frac{Complex\ Words}{Total\ Number\ of\ Words}\right)\right)$$

The results obtained from the Gunning Fog Index analysis are shown in Table 5.

Table 5: Gunning Fog Index Results

	Average Word Variety	Average Complex Word Ratio	Average Gunning Fog Index
Fake Reviews	0.834	0.123	8.78
Real Reviews	0.703	0.118	9.97
Artificial Intelligence Generated Reviews	0.841	0.171	9.16

The results show that fake comments have high word diversity, are the simplest and most easily understandable comments. Gunning Fog Index values indicate how many years of education a person can easily read and understand the text. Therefore, for a person with 8 years of education, the fake comments in the data set are readable. It has been determined that real comments are more complex and difficult to read. Real comments, which are the comments with the least word diversity, require more cognitive load than fake and AI-generated comments. It has been determined that artificial intelligence comments are slightly simpler than real comments and slightly more complex than fake comments. The highest value in terms of average word diversity was obtained in comments generated by AI. These results also support the inferences about the complexity of real comments.

One of the most controversial analyzes is the measurement of the frequency of use of personal pronouns in texts. There are many different conclusions in the literature on this issue. According to a number of studies, the frequent use of the first-person singular pronoun is a feature of deceptive interpretations that are made to mimic personal experiences (Ott et al., 2011; Lee et al., 2009; Louwerse et al., 2010; Li et al., 2014). In contrast, other studies have identified the low frequency of use of the first-person singular as a feature of deceptive interpretations (Hancock et al., 2007; Mihalcea & Strapparava, 2009; Newman et al., 2003). In contrast, Swol et al. (2012) claimed that deceivers use a high rate of third person pronouns. According to some authors, since there are many different opinions about the use of personal pronouns, it is stated that the use of pronouns may not be a reliable indicator for detecting fake texts (Gröndahl and Asokan, 2019). Differences in language structure and cultural differences make it difficult to express the meaning of such features in a general framework. There are some limitations for conducting this analysis in Turkish. Turkish is a language where the use of hidden subjects is very common, and in this case, it is not possible to count personal pronouns with word counting tools. Therefore, the dataset was translated into English in order to perform this analysis. Another constraint is that since the real comments are longer comments, all personal pronouns will normally be used more frequently than others. In order to prevent any potential for misleading results in the analysis, the frequency of pronoun use was normalized by taking the length of the comments into account. First, the number of words in each comment was calculated. Then, the number of pronouns in a comment was determined. The pronoun frequency was calculated as expressed in Figure 2. In the next step, pronoun frequency was normalized by comment length. This allowed us to determine the average frequency of pronoun use per comment.

Figure 2: Pronoun Frequency Calculation

$$Pronoun\ Frequency = \frac{Number\ of\ Pronouns}{Comment\ Length}$$

Finally, the pronoun frequencies for each label (fake, real, AI) are averaged. The way the pronoun frequencies are averaged is expressed in Figure 3.

Figure 3: Average Pronoun Frequency Calculation

$$Average\ Pronoun\ Frequency = \frac{\sum_{i=1}^{n}\left(\frac{Number\ of\ Pronouns_i}{Comment\ Length_i}\right)}{N}$$

The results of the analysis are shown in Table 6.

Table 6: Frequency of Use of Pronouns

Label	I	you	he	she	it	we	they	me	him	her	us	them
Fake	0.02563	0.01063	0.00106	0.00007	0.02288	0.01592	0.00701	0.00244	0.00020	0.00001	0.00226	0.00095
Real	0.01692	0.01458	0.00107	0.00025	0.01775	0.01807	0.00636	0.00131	0.00033	0.00027	0.00272	0.00123
AI	0.00593	0.00000	0.00000	0.00000	0.00621	0.02676	0.00000	0.00170	0.00000	0.00000	0.00138	0.00000

It was found that "I" and "it" pronouns were used more frequently in fake reviews. This suggests that fake reviews are often written using phrases that emphasize personal experiences and talk about the general features of the hotel. People who write fake reviews may tend to emphasize personal experiences to be more convincing. Looking at the literature, even though the first-person singular is more representative of truthfulness rather than deception in most studies, there are also many studies where these results are similar. The pronouns "we", "it", "I" and "you" are the most commonly used pronouns in real comments. Real comments have a more balanced distribution. The results here are based on the desire of the real commenters to express themselves in more detail and in a variety of ways. Real reviewers talk about both their own experiences and the hotel in detail. An analysis of the frequency of pronouns used by artificial intelligence reveals that the pronoun "we" is particularly prevalent. This shows that the AI generally uses a language pattern that emphasizes group experiences when creating reviews.

4. CONCLUSION

The objective of this study is to create a dataset for the detection of deception in the Turkish language. Although there are datasets for deception detection in several languages, including English, Chinese, Arabic, Italian and Spanish, there is a lack of a comprehensive dataset in Turkish. To overcome this deficiency, a dataset containing a total of 5013 hotel reviews from three different sources was created. The dataset is completely balanced and is also divided into positive and negative reviews. While creating the data set, the study was carried out by considering the methods of the studies accepted in the literature on this subject and the special situations of the Turkish language.

The findings of this study showed remarkable similarities and differences when compared with the studies in the literature. For example, Ott et al. (2011, 2013) found that real reviews are longer and more detailed than fake reviews in English. Similarly, in this study, in the context of Turkish hotel reviews, real reviews were found to be longer than fake and AI-generated reviews. This finding suggests that linguistic complexity and text length can be an important indicator for detecting deceptive texts, regardless of language. However, the findings of the study show some differences with the findings of Ignat et al. (2024) on AI-generated texts. Ignat et al. concluded that AI-generated fake texts are more complex and richer in diversity than real texts. According to the findings in this study, the AI-generated Turkish comments were found to be shorter and less detailed compared to the fake and real comments. This suggests that the language production capacity of artificial intelligence may differ depending on the structural features and complexity of the language.

The results show that Turkish text-based deception detection studies are feasible. Real reviews were found to be significantly longer and more detailed than fake and AI-generated fake reviews. This finding is consistent with the literature suggesting that real reviews generally contain more information and detail. The Gunning Fog Index results show that fake reviews are simpler and easier to understand, while real reviews are more complex and harder to read. This suggests that real reviews require more cognitive effort and that fake reviews often contain more superficial and generalized statements. In the pronoun usage analysis, it was found that the pronouns "I" and "he" were used more frequently in the fake reviews, while the real reviews showed a more balanced distribution of pronouns. The prominence of the pronoun "we" in AI-generated reviews indicates that these reviews generally emphasize group experiences.

In the studies conducted in Turkish, it is seen that fake news detection studies are mostly conducted in which data can be obtained more easily. However, there is a need for more diverse data sets and studies in the Turkish literature on deception detection, which has been studied with many different types of data in the literature. With this study, an important step has been taken towards providing a reliable data set for deception detection in Turkish. Compared to other studies in the literature, the most important contribution of this study is the creation of a dataset on deception detection in Turkish. While there are studies in English, Chinese, Spanish and many other languages in the literature, there is no such study in Turkish language, which makes this study unique and contributes to the literature. Moreover, the comparison of real, fake and AI-generated comments adds a new dimension to deception detection studies. In the future, it is aimed to develop more comprehensive analyzes and advanced algorithms using this dataset. In addition, cultural differences can also be revealed by comparing deception detection studies across different languages and cultures. With this dataset, it will be possible to detect deceptive statements in Turkish texts using machine learning algorithms. Thus, as in other languages, Turkish natural language processing studies will be able to make progress in the detection of deceptive statements, and it will be possible to develop the literature.

It is clear that the detection of fake reviews will provide significant benefits to the strategic management processes in the hospitality industry and other service sectors. Hospitality companies can maintain customer satisfaction and trust by preventing the negative effects of fake reviews on the brand. Identifying these comments supports businesses to achieve sustainable growth targets by improving crisis management processes. In addition, filtering fake reviews in long-term strategic planning contributes to directing resources to the right areas and helps businesses to manage cost-effectively. Fake positive reviews can mislead customer expectations and lead to marketing messages that do not match service experiences. This can lead to customer loss and negative feedback. Detection of fake negative reviews offers businesses the opportunity to protect their reputation and gain strategic advantage in times of crisis. Making strategic decisions based on real customer reviews provides businesses with an environment of transparency and trust, thus creating a positive experience for both employees and customers. Although a data set for the tourism sector was created in this study, deception detection studies have the potential to be used in strategic management and decision-making processes not only in the tourism sector but also in other service sectors.

REFERENCES

Catelli, R., Bevilacqua, L., Mariniello, N., Di Carlo, V. S., Magaldi, M., Fujita, H., De Pietro, G., & Esposito, M. (2023). A new Italian cultural heritage data set: Detecting fake reviews with BERT and ELECTRA leveraging the sentiment. IEEE Access, 11, 52214–52225.

Ekman, P., & O'Sullivan, M. (1991). Who can catch a liar? American psychologist, 46(9), 913.

Esmaeili, N. (2015). Strategic management and its application in modern organizations. International Journal of Organizational Leadership, 4, 118-126.

Gröndahl, T., & Asokan, N. (2019). Text analysis in adversarial settings: Does deception leave a stylistic trace?. ACM Computing Surveys (CSUR), 52(3), 1-36.

Hammad, A. A., & El-Halees, A. (2013). An approach for detecting spam in Arabic opinion reviews. The International Arab Journal of Information Technology, 12.

Hancock, J. T., Thom-Santelli, J., & Ritchie, T. (2004). Deception and design: The impact of communication technology on lying behavior. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 129–134.

Hancock, J. T., Curry, L. E., Goorha, S., & Woodworth, M. (2007). On lying and being lied to: A linguistic analysis of deception in computer-mediated communication. Discourse Processes, 45(1), 1-23.

Ignat, O., Xu, X., & Mihalcea, R. (2024). MAiDE-up: Multilingual deception detection of GPT-generated hotel reviews. arXiv preprint arXiv:2404.12938.

Lee, C. C., Welker, R. B., & Odom, M. D. (2009). Features of computer-mediated, text-based messages that support automatable, linguistics-based indicators for deception detection. Journal of Information Systems, 23(1), 5-24.

Li, H., Chen, Z., Liu, B., Wei, X., & Shao, J. (2014). Spotting fake reviews via collective positive-unlabeled learning. 2014 IEEE International Conference on Data Mining, 899–904.

Li, J., Ott, M., Cardie, C., & Hovy, E. (2014). Towards a general rule for identifying deceptive opinion spam. Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), 1566–1576.

Louwerse, M., Lin, D., Drescher, A., & Semin, G. (2010). Linguistic cues predict fraudulent events in a corporate social network. Proceedings of the Annual Meeting of the Cognitive Science Society, 32(32).

Markowitz, D. M., & Hancock, J. T. (2014). Linguistic traces of a scientific fraud: The case of Diederik Stapel. PloS one, 9(8), e105937.

Mihalcea, R., & Strapparava, C. (2009, August). The lie detector: Explorations in the automatic recognition of deceptive language. Proceedings of the ACL-IJCNLP 2009 Conference Short Papers, 309–312.

Mukherjee, A., Venkataraman, V., Liu, B., & Glance, N. (2013). What Yelp fake review filter might be doing? Proceedings of the International AAAI Conference on Web and Social Media, 7(1), 409–418.

Newman, M. L., Pennebaker, J. W., Berry, D. S., & Richards, J. M. (2003). Lying words: Predicting deception from linguistic styles. Personality and social psychology bulletin, 29(5), 665-675.

Ott, M., Choi, Y., Cardie, C., & Hancock, J. T. (2011). Finding deceptive opinion spam by any stretch of the imagination. arXiv preprint arXiv:1107.4557.

Ott, M., Cardie, C., & Hancock, J. T. (2013). Negative deceptive opinion spam. Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 497–501.

Patchin, J. W., & Hinduja, S. (2010). Cyberbullying and self-esteem. Journal of School Health, 80(12), 614–621.

Salminen, J. (2024, March 20). Fake reviews dataset. OSF. Retrieved July 8, 2024, from osf.io/tyue9.

Van Dinh, C., Luu, S. T., & Nguyen, A. G. T. (2022). Detecting spam reviews on Vietnamese e-commerce websites. Asian Conference on Intelligent Information and Database Systems, 595–607. Springer International Publishing.

Viji, D., Gupta, N., & Parekh, K. H. (2022). History of deception detection techniques. Proceedings of the International Conference on Deep Learning, Computing and Intelligence: ICDCI 2021, 373–387. Springer.

Vrij, A., Mann, S. A., Fisher, R. P., Leal, S., Milne, R., & Bull, R. (2008). Increasing cognitive load to facilitate lie detection: The benefit of recalling an event in reverse order. Law and Human Behavior, 32, 253–265.

Whitty, M. T., & Buchanan, T. (2012). The online romance scam: A serious cybercrime. CyberPsychology, Behavior, and Social Networking, 15(3), 181–183.

Xu, Y., Shi, B., Tian, W., & Lam, W. (2015). A unified model for unsupervised opinion spamming detection incorporating text generality. Twenty-Fourth International Joint Conference on Artificial Intelligence.