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BIBLIOMETRIC ANALYSIS OF THE USE OF SENTIMENT ANALYSIS IN THE CONTEXT OF SERVICE QUALITY

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Abstract: It is observed that sentiment analysis studies are increasing day by day. Sentiment analysis technique was born in computer sciences, and since the technique can be used in different fields, researchers have started to use this technique in different disciplines. With the increase in competition, businesses have realized that they need to improve service quality in order to satisfy their customers. The ability to process the data generated by the digitalization of human behavior with emotion analysis has become an important factor in determining service quality for businesses. In this study, bibliometric analysis was conducted to determine the place of sentiment analysis in the literature in the context of service quality. Within the scope of the study, 2538 articles related to the search word "sentiment analysis" and 23 articles with the search words "sentiment analysis and service quality" were analyzed in the WoS database between 2008 and 2022. Then, a bibliometric analysis was conducted on the use of sentiment analysis with service quality and a literature evaluation of the sentiment analysis technique in the context of service quality was conducted. In addition to bibliometric analyses, the titles and abstracts of emotion analysis studies in the context of emotion analysis and service quality were examined by content analysis in order to determine the study topics and techniques. It was noteworthy that the use of emotion analysis technique in the field of service quality started in 2016 and that the studies in this field are still few and used in certain sectors.

Keywords: sentiment analysis, service quality, bibliometric, content analysis

HİZMET KALİTESİ BAĞLAMINDA DUYGU ANALİZİ KULLANIMINA YÖNELİK BİBLİYOMETRİK ANALİZ

Özet: Duygu analizi çalışmalarının günden güne arttığı gözlenmektedir. Duygu analizi tekniği bilgisayar bilimleri içerisinde doğmuştur, tekniğinin farklı alanlarda kullanılabilir olmasıyla araştırmacılar farklı disiplinlerde bu tekniği kullanmaya başlamışlardır. İşletmeler, rekabetin artmasıyla birlikte müşterilerini memnun edebilmek için hizmet kalitesini arttırması gerektiğini anlamışlardır. İnsan davranışlarının dijitalleşmesiyle oluşan verinin duygu analiziyle işlenebilmesi, işletmeler açısından hizmet kalitesinin tespitinde önemli bir unsur haline gelmiştir. Bu çalışmada hizmet kalitesi bağlamında duygu analizinin

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literatürdeki yerinin belirlenebilmesi için bibliyometrik analizler yapılmıştır. Çalışma kapsamında WoS veri tabanında 2008-2022 yılları arasında "duygu analizi" arama kelimesiyle ilişkili 2538 makale, "duygu analizi ve hizmet kalitesi" arama kelimeleriyle 23 makale analize tabi tutulnuştur. öncelikle duygu analiziyle ilgili çalışmalarının bibliyometrik analizi yapılmıştır. Daha sonra ise duygu analizinin hizmet kalitesiyle kullanımına yönelik bibliyometrik analiz yapılarak duygu analizi tekniğinin hizmet kalitesi bağlamında literatür değerlendirilmesi yapılmıştır. Bibliyometrik analizlerin yanı sıra duygu analizi ve hizmet kalitesi bağlamında duygu analizi çalışmalarının başlık ve özetleri çalışma konularını ve tekniklerini belirleyebilmek amacıyla içerik analiziyle incelenmiştir. Hizmet kalitesi alanında duygu analizi tekniğinin kullanımının 2016 yılında başladığı ve bu alanda yapılan çalışmaların henüz az olduğu ve belirli sektörlerde kullanıldığı dikkat çekmiştir.
Anahtar Kelimeler: duygu analizi, hizmet kalitesi, bibliyometrik, içerik analizi

1. INTRODUCTION

Bibliometrics is the application of mathematical and statistical methods to books and other communication media. It is also mentioned that the concept was used in the book "Statistical bibliography about the growth of modern civilization" by E. Wyndham Hulme, which was taught in the Bibliography course at Cambridge University in 1922 [1].

The first examples of systematic data collection were provided by Alfred Lotka and Samuel Bradford. In 1955, Eugene Garfield developed the "Science Citation Index" (SCI), which made it possible to systematically track citations and marked the beginning of a new era in bibliometrics [2].

Bibliometric analysis is a type of analysis that uses numerical data to study the literature, researchers, journals, and research topics [3]. It is a type of analysis that is used to reveal the focus of research and to measure and evaluate the scientific output [4]. Similarly, the discipline of bibliometrics is the application of mathematical and statistical methods to scientific publications [2]. Bibliometrics is the study of quantitative analysis and statistics of similar publications such as articles [5].

Bibliometric analysis is important for identifying the level of development of various sources published in any field [6]. Bibliometric studies are becoming increasingly popular [7]. There are approximately 17.500 bibliometric studies in the Scopus database [2].

Bibliometric analysis is a technique used to carry out the quantitative and qualitative analysis of studies in each field, to identify leading figures, to identify important researchers in the field of study, and to follow the development of the subject over the years. The technique reveals characteristics such as the disciplines in which the subject of the bibliometric analysis has been studied, the journals in which it has been published, and the keywords. Although the origins of bibliometrics go back to the 1920s, studies in literature have continued to increase since the 2000s.

To perform bibliometric studies, data must be collected. Web of Science (WoS) is one of the academic databases from which these data can be obtained. WoS is a citation database for bibliometric studies that was established under the name Institute for Scientific Information in 1960 and was included in Thomson Reuters publications in 1992 [8]. WoS provides a range of meta-data to researchers interested in bibliometric analysis, including abstracts, citations, lists of authors, institutions, countries, and impact factors of the journal for publications included in the relevant indices [9].

The Web of Science database is a preferred source for content analysis because it does not have incomplete reference lists [10]. VOSviewer is a program developed by Ness Jan van Eck and Ludo Waltman that is capable of visually representing literature, keywords, authors, and similar topics in a networked format [11]. VOSviewer and other bibliometric tools, as well as research databases like the Web of Science, are effective methods for discovering and analyzing large amounts of research data for bibliometric analysis [12].

MAXQDA is a software package that is used in qualitative data analysis and text mining, allowing for in-depth analysis of content. It is often used in studies involving the content analysis and is a useful tool for discovering and analyzing large amounts of research data in fields such as bibliometrics. It is a powerful tool for exploring and understanding complex data sets and can be used to identify patterns, trends, and relationships within the data. Some common applications of MAXQDA include coding and categorizing text data, creating and analyzing word clouds, creating visualizations of data, and conducting content analysis.

Sentiment analysis is a subfield of natural language processing (NLP) that seeks to identify and extract subjective information from text data [13]. It is often used to analyze customer feedback, social media posts, and other forms of written or spoken communication to understand the emotional tone or attitude of the speaker or writer. As the spread of Web 2.0 and the increase in the use of social media has enabled people to share their opinions more, it has become possible to collect and use these opinions for the service and business industry [14]. Service quality is a concept related to the ease of the customer's purchasing experience, the politeness of the behavior of the service provider, the expertise and familiarity of the business employees with the subject matter they are serving, the ability of the service provider to show empathy, and, in short, how well the service provider can meet the customer's needs [15]. Sentiment analysis can be used to evaluate the quality of a service by analyzing customer feedback and other forms of written or spoken communication about the service. This can be particularly useful for organizations that want to understand the emotional tone or attitude of their customers towards the service, as it can provide insight into areas of the service that are particularly important to customers and areas that may be causing frustration or dissatisfaction.

To use sentiment analysis to evaluate service quality, an organization would typically gather a dataset of customer feedback about the service, such as social media posts, reviews, or survey responses. This dataset would then be labeled by humans or by an automated machine learning algorithm as positive, negative, or neutral based on the emotional valence of the text. This study aims to determine the place of sentiment analysis and studies on service quality using sentiment analysis in the literature. In addition, it aims to reveal the position of researchers, countries, and publishers who conduct sentiment analysis. The following questions will be answered to achieve the aim of the research: What are the citation network, author network, productive authors, and keywords of sentiment analysis studies? What is the disciplinary distribution of sentiment analysis studies? What are the citation network, author network, productive authors, and keywords of service quality studies in the context of sentiment analysis? What is the disciplinary distribution of service quality studies in the context of sentiment analysis? How is the abstract and keyword content analysis of sentiment analysis studies conducted? How is the abstract and keyword content analysis of service quality studies in the context of sentiment analysis conducted?

2. METHOD

The data collection for answering the research questions and achieving the aim of the study was conducted in the WoS core collection database. The search query 'TI=("sentiment analysis") AND

DT=(Article)' was used in the WoS database to collect articles with the title of sentiment analysis. To identify studies using the sentiment analysis and service quality keywords, the search query 'TI=("sentiment analysis") AND TS=("service quality")' AND DT=(Article)" was used. This query resulted in articles with the title sentiment analysis and the subject title service quality. The collected data was analyzed using the Office 365 Excel package, the VOSviewer 1.6.18 network analysis program, and the MAXQDA 2022 content analysis program. The Office 365 Excel program was used to draw various graphs of the studies. The VOSviewer 1.6.18 program was used to visualize citation networks. The MAXQDA 2022 program was used to conduct the abstract and keyword content analysis of the collected studies.
Network analysis of the studies obtained will be done with VOSviewer program. With MAXQDA program, the area of concentration of the studies, the techniques and keywords used in the studies will be revealed.

3. FINDINGS

As a result of the query made in the WoS academic database, 2538 articles were accessed between 2008 and 2022. The distribution of the articles according to the years is shown in Figure 1. The fact that research on the subject of sentiment analysis started in 2008 and has been increasing in frequency since 2015 indicates that sufficient saturation has not yet been reached in this field of study.

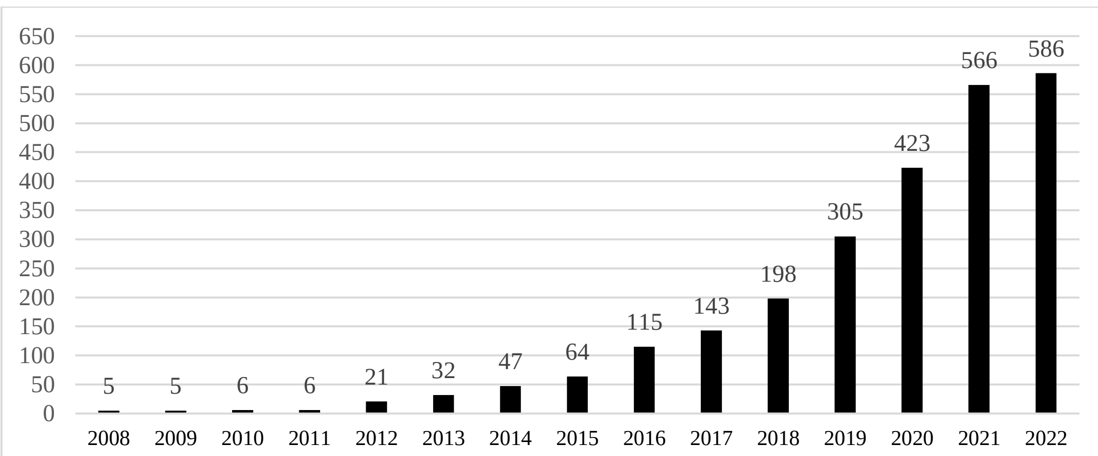

Figure 1. Number of Sentiment Analysis Articles by Year

In Figure 2, the number of publications according to discipline category is shown. Most publications were made in the fields of computer science-artificial intelligence, computer science-theoretical methods, and computer science-information systems. However, there are also studies in the fields of electrical and electronic engineering, computer science-interdisciplinary applications, telecommunications, computer science-software engineering, linguistics, computer science-hardware architecture, and interdisciplinary engineering.

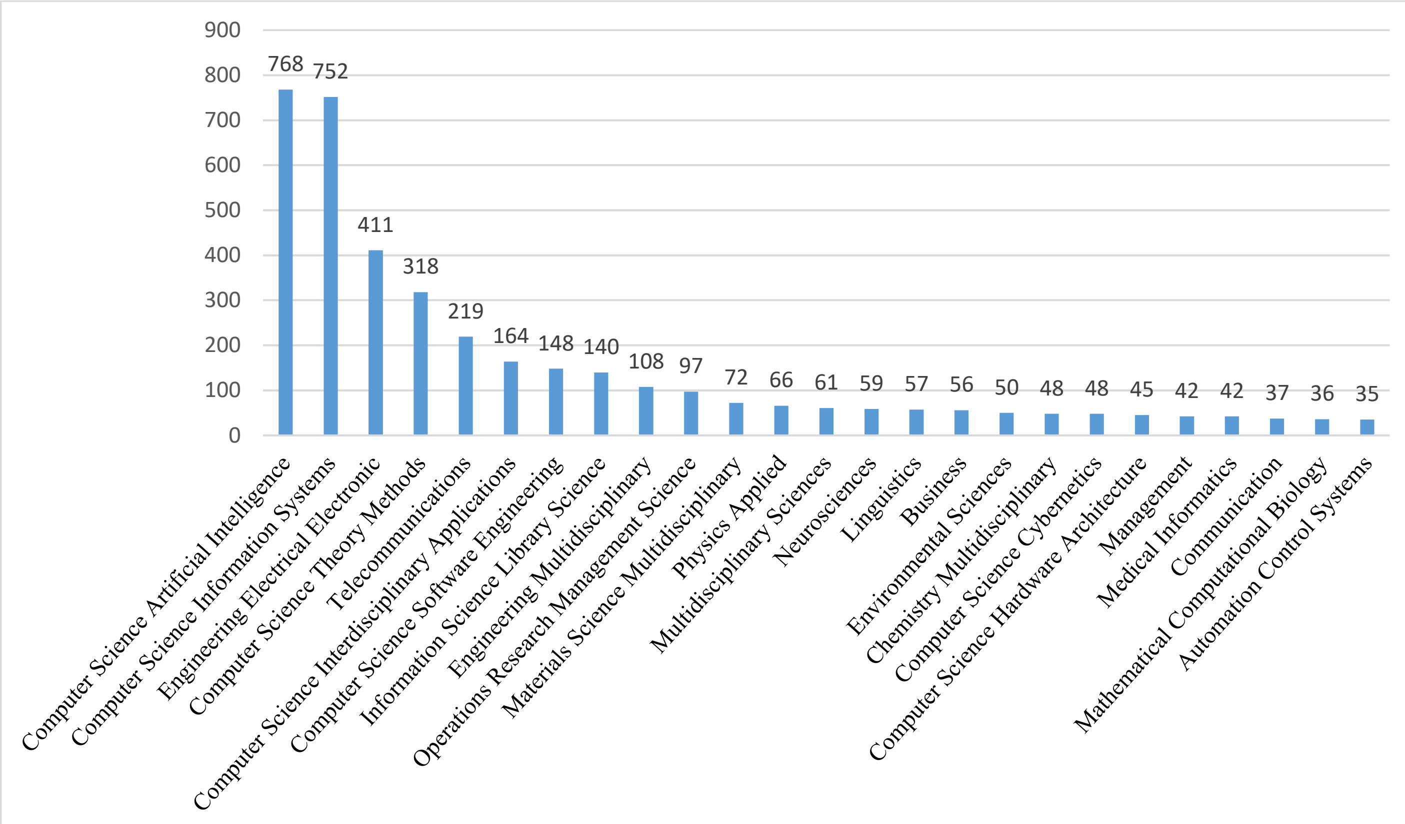

Figure 2. Number of Publications According to Discipline Category

Table 1. Top Ten Authors According to Link Strength

Author Name	Number of Publications	Number of Citations	Total Link Strength
Cambria, Erik	32	3020	3076
Hussain, Amir	16	884	1016
Poria, Soujanya	11	1119	1016
Taboada, Maite	4	1409	983
Brooke, Julian	1	1359	924
Stede, Manfred	1	1359	924
Tofiloski, Milan	1	1359	924
Voll, Kimberly	1	1359	924
Hassan, Ahmed	1	964	780
Korashy, Hoda	1	964	780
Medhat, Walaa	1	964	780

Upon examining the studies obtained, it was determined that a total of 7329 authors worked on sentiment analysis. Table 1 lists the top 11 authors according to total link strength. Total link strength is a value calculated by the number of common studies with other authors and the citations obtained from these studies [11]. Table 2 lists the authors with the most publications. As seen in Table 1, some authors have only one publication, but their number of citations and total link strength is higher than those of the top ten authors with multiple publications in Table 2. This shows that the authors in Table 1 have a better position in the literature on sentiment analysis and that the publications they have made with each other are effective.

Table 2. Authors with the Most Publications

Author Name	Number of Publications
Cambria, E.	32
Hussain, A.	16
Li, X.	13
Kumar A	12
Li, Y.	12
Poria, S.	12
Kumar, S.	11
Yang, J.	11
Gelbukh, A.	10
Wang, J.	10

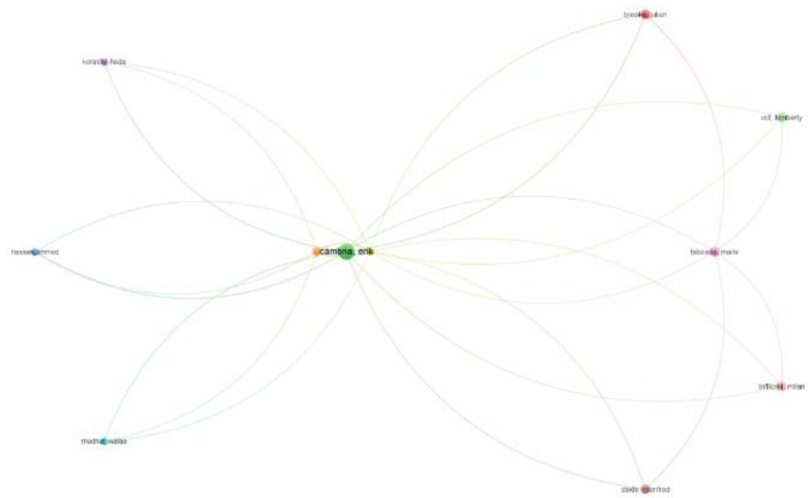

Figure 3. Network of the Top Eleven Authors with the Highest Link Strength

Figure 3 shows the network among the top eleven authors with the highest link strength. Hussain, A. and Cambira, E. are centrally located due to both their high number of publications and their high number of citations. The high link strength of these authors, particularly Hussain, A. and Cambria, E., has been identified as prominent in sentiment analysis studies. Of the 2538 related studies, 574 received no citations, and the average number of citations per study was calculated as 18.5. Table 3 lists the top ten studies with the most citations.

Table 3. Top Ten Articles According to Number of Citations

Author Name	Article Title	Number of Citations	Year of Publication
Taboada, Maite; Brooke, Julian; Tofiloski, Milan; Voll, Kimberly; Stede, Manfred	Lexicon-Based Methods for Sentiment Analysis	1430	2011
Medhat, Walaa; Hassan, Ahmed; Korashy, Hoda	Sentiment Analysis Algorithms and Applications: A Survey	995	2014
Ravi, Kumar; Ravi, Vadlamani	A Survey on Opinion Mining and Sentiment Analysis: Tasks, Approaches, and Applications	625	2015
Abbasi, Ahmed; Chen, Hsinchun; Salem, Arab	Sentiment Analysis In Multiple Languages: Feature Selection for Opinion Classification in Web Forums	610	2008

Cambria, Erik; Schuller, Bjoern; Xia, Yunqing; Havasi, Catherine	New Avenues in Opinion Mining and Sentiment Analysis	586	2013
Kiritchenko, Svetlana; Zhu, Xiaodan; Mohammad, Saif M.	Sentiment Analysis of Short Informal Text	416	2014
Chen, Tao; Xu, Ruifeng; He, Yulan; Wang, Xuan	Improving Sentiment Analysis via Sentence Type Classification Using Bilstm-CRF And CNN	379	2017
Prabowo, Rudy; Thelwall, Mike	Sentiment Analysis: A Combined Approach	366	2009
Schouten, Kim; Frasincar, Flavius	Survey On Aspect-Level Sentiment Analysis	316	2016
Li, Nan; Wu, Desheng Dash	Using Text Mining And Sentiment Analysis for Online Forums Hotspot Detection And Forecast	292	2010

The study of researchers who propose a dictionary-based method for sentiment analysis is the most cited study in this field. In their study, they developed a dictionary consisting of marked words using a semantic method called SO-CAL. With the help of this dictionary, they have performed sentiment analysis from texts [16].

This study presents a summary of the studies on algorithms and applications used in sentiment analysis. The researchers state that the most used machine learning algorithms in the 54 papers on sentiment analysis and sentiment classification are Support Vector Machines and Naive Bayes algorithms. They also discuss notable new topics related to sentiment analysis in their studies [17].

In this study, 161 articles published on sentiment analysis between 2002 and 2015 are classified according to machine learning, natural language processing techniques, and sentiment analysis applications [18].

In this study conducted in 2008, data obtained from a film review site was subjected to sentiment analysis using Support Vector Machines and Entropy Weighted Genetic Algorithm techniques [19].

Cambria et al. [20] have identified the differences and commonalities between sentiment analysis and opinion mining and have presented new opportunities in this field. In this study, a machine learning algorithm with an F score of 89.5% was developed by performing sentiment analysis on informal texts such as short messages and tweets using the training set developed [21]. Chen et al. [22] have classified sentences into four different sensitivity sets using three artificial neural network-based models they developed. In this way, they have developed a method that performs better sentiment analysis on complex sentences.

Prabowo and Thelwell [23] have argued that they have developed a non-automatic method that aims to use trained data sets, rule-based classification, and machine learning techniques together in sentiment analysis. In their study, they processed data from movie reviews, product reviews, and the Myspace website. They claim to have achieved a better F1 score in their proposed model.

Schouten and Frasincar [24] have classified the studies on sentiment analysis as frequency-based, punctuation-based, supervised machine learning, unsupervised machine learning, hybrid, and dictionary-based techniques. They have also compared the data sources and performances of the studies.

Li and Wu [25] processed 220,053 posts on 31 different topics using a sentiment analysis technique from a forum site. They classified the processed data using K-means and Support Vector Machine algorithms. When the network of the most cited publications in Figure 4 is examined, it is observed that the study by Abbasi et al. [19] has no relationship with other studies. Other authors have not cited this study.

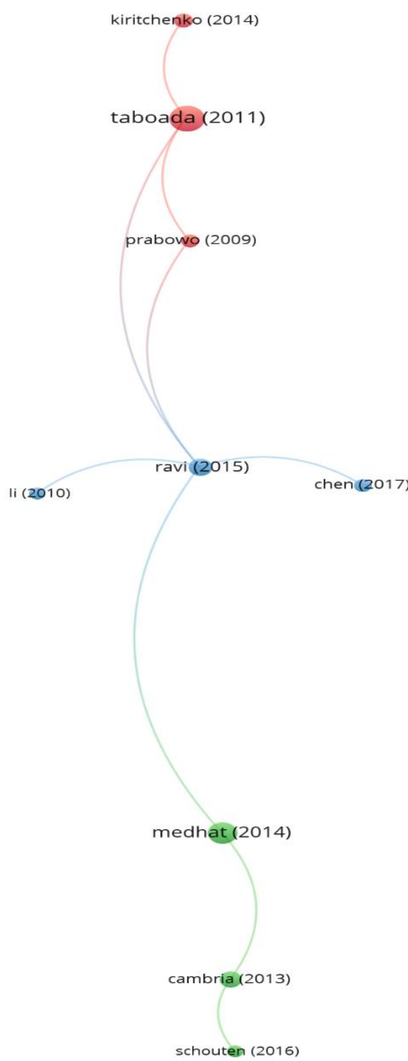

Figure 4. Network of Most Cited Documents

Table 4 shows the top ten countries based on the total connection strength of sentiment analysis studies published. Out of the 2538 publications, 104 were published in different countries. In the field of sentiment analysis, the People's Republic of China (PRC), India, and the United States of America (USA) are observed to have high numbers of studies, high total connection strengths, and high performance in this field.

Table 4. Most Influential Countries Table

Country	Number of Publications	Number of Citations	Total Link Strength
PRC	655	10238	3830
India	400	4355	3015

USA	265	9681	1907
Singapore	54	3257	1382
England	120	3602	1229
Spain	151	3193	1140
Saudi Arabia	148	1624	1001
Canada	74	3445	921
Pakistan	115	1576	918
Germany	44	2834	737

Although the references to studies originating from the USA are high, the total link strength of Indian authors is higher due to their higher collaboration with each other. The average number of references for studies originating from China is 15.6, the average number of references for studies originating from India is 10.8, and the average number of references for studies originating from the United States is 36.5. The highest average number of references is observed in studies conducted in Singapore with 60.3.

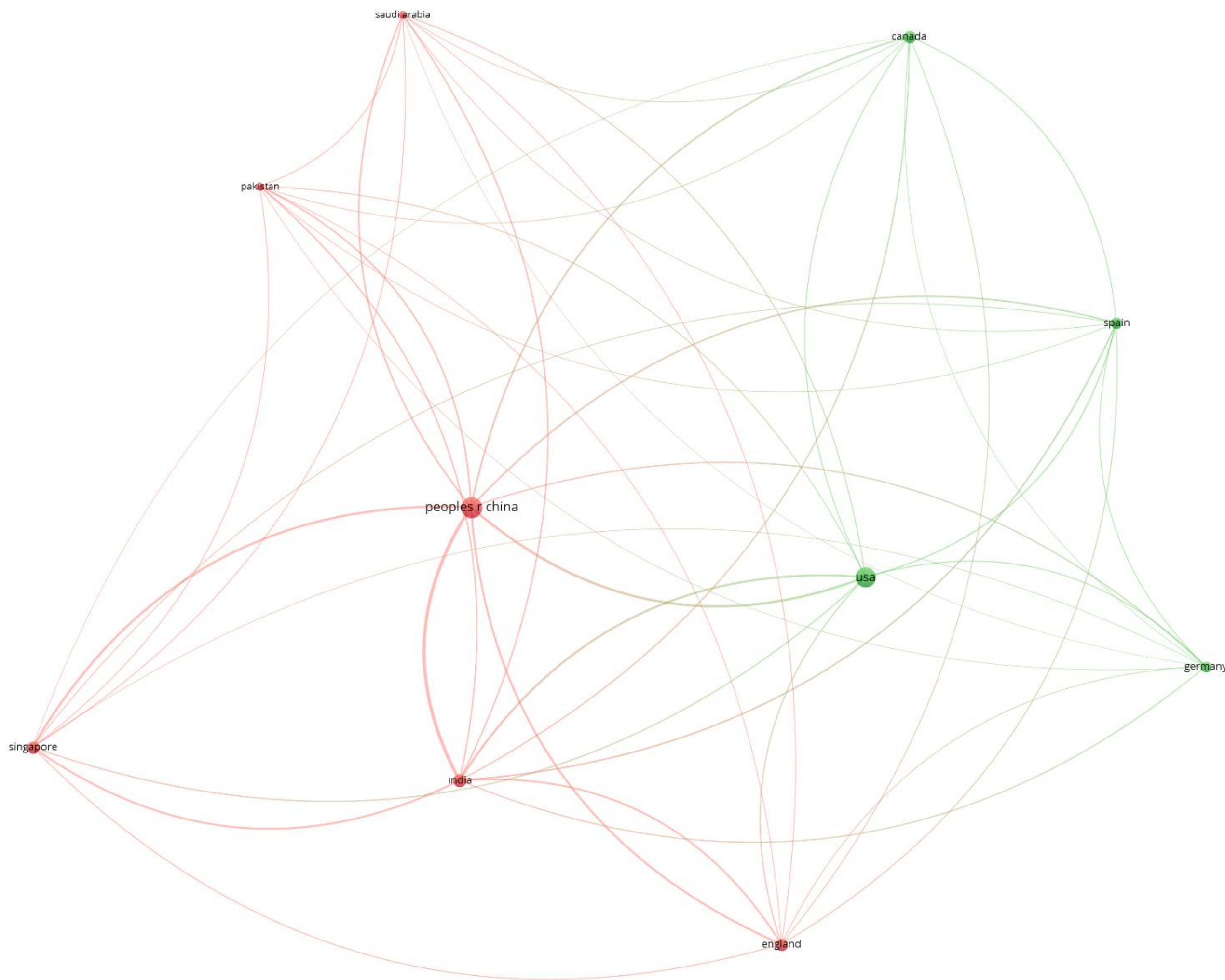

Figure 5. Citation Network by Country

Upon examining the relevant studies based on country, it is observed that there is a connection between 97 out of 104 different countries, while there are seven countries that do not have connections with these

countries or with each other. These countries that do not have connections with each other or with other countries are Scotland, Luxembourg, Peru, Cameroon, Bosnia, and Herzegovina, Syria, and Albania.
The first ten journals with the highest total link strength are listed in Table 5. The relevant articles have been published in 797 different journals. Sentiment analysis-related studies have been published most frequently in the IEEE Access journal and it is the journal with the highest total link strength. In the network analysis of the journals shown in Figure 6, connections between all of the journals can be seen. This indicates that the citations of the published studies are mutual among the journals. When considering all 797 journals, it has been determined that 635 of these journals have connections with each other and 162 of them do not have connections with these journals. The studies in these journals have not received citations from studies published in other journals.

Table 5. List of Journals with the Highest Link Strength

Source	Number of Publications	Number of Citations	Total Link Strength
IEEE Access	140	1997	925
Knowledge-Based System	66	3048	830
Expert Systems with Application	57	3048	679
Information Processing & Management	35	1430	479
Neurocomputing	37	1126	335
Artificial Intelligence Review	20	466	315
Cognitive Computation	26	765	309
Computational Linguistics	2	1628	308
Future Generation Computer Systems	13	679	294
IEEE Intelegent System	14	1592	283

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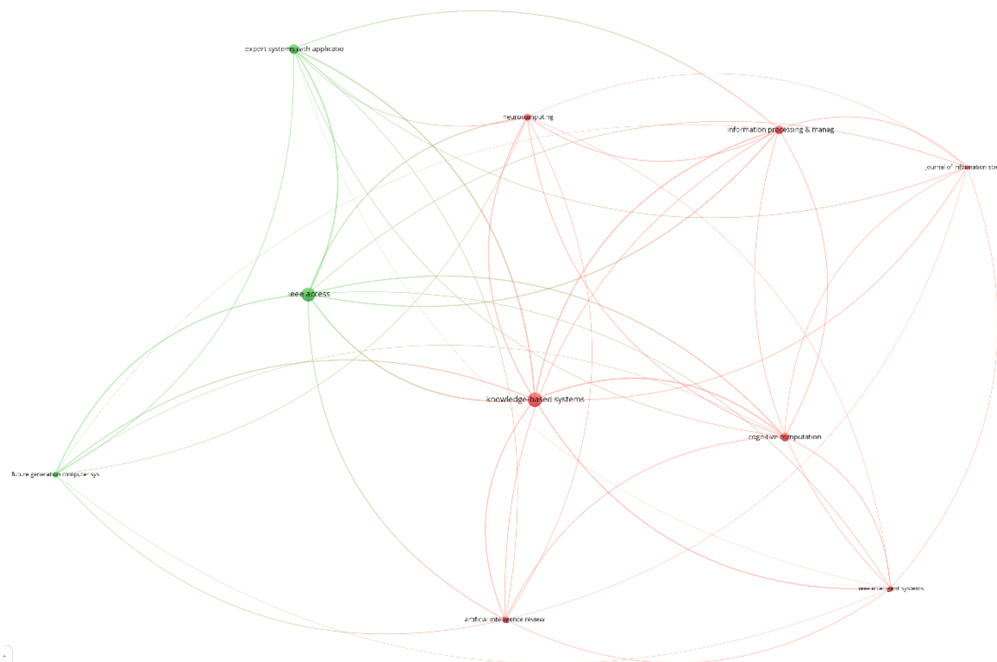

Figure 6. Top Ten Source Network Analysis of Sentiment Analysis Studies

A keyword analysis study was conducted using VOSviewer 1.6.18 and 5040 keywords were identified. The keywords with the highest total link strength are listed in Table 6. Machine learning, deep learning, Twitter, natural language processing, opinion mining, social media, text mining, Covid-19, and feature extraction are the most common and related keywords used in sentiment analysis studies.

Table 6. Keyword Total Link Strength Table

Keywords	**Number of Identified Publications**	**Total Link Strength**
Sentiment Analysis	1614	7548
Machine Learning	283	1466
Deep Learning	260	1325
Twitter	241	1292
Natural Language Processing	237	1187
Opinion Mining	217	1017
Social Media	193	979
Text Mining	113	555
Covid-19	102	620
Feature Extraction	69	545

In the MAXQDA 2022 program, keywords are handled separately as words. When the keywords obtained from the related studies are subjected to content analysis with the MAXQDA 2022 program, the keyword frequency table in Table 7 is formed. After the words 'analysis' and 'sentiment', the words 'learning', 'mining', 'social', 'machine', 'language', 'deep', 'network', 'nervous', 'text', and 'Twitter' come. When this frequency table is examined, it can be said that the studies on sentiment analysis are intense in social media, especially Twitter, and that sentiment analysis is used together with the text mining technique.

In sentiment analysis, various artificial intelligence techniques are used. When the keywords of the studies are examined, it is observed that machine learning, artificial neural networks, and deep learning techniques are at the forefront.

Table 1. Keyword Frequency Table

Keyword	Frequency	%
analysis	2482	9,68
sentiment	2441	9,52
learning	834	3,25
mining	447	1,74
social	447	1,74
machine	397	1,55
language	370	1,44
deep	327	1,28
network	316	1,23
neural	304	1,19

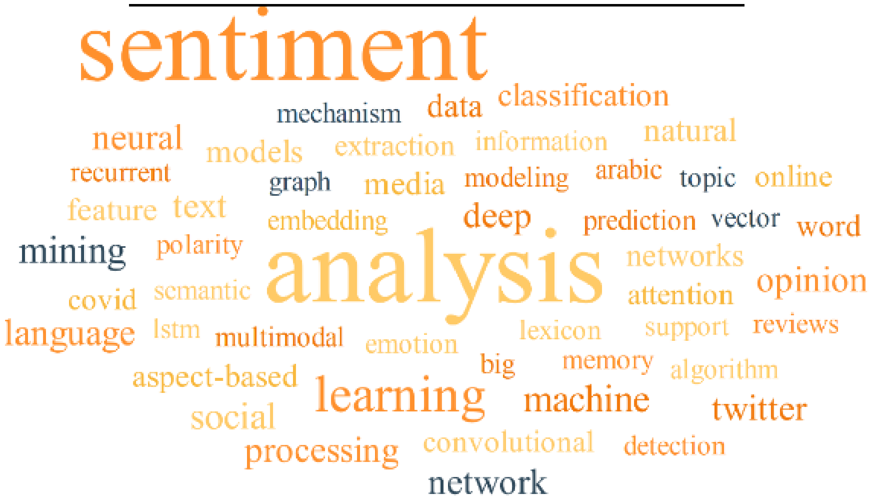

Figure 7. Keywords Word Cloud

The word cloud consisting of the first 50 keywords according to frequency is shown in Figure 6. Here, the words "support vector machine", "lexicon", and "classification", which are used in sentiment analysis techniques, and the word "covid", which appears frequently due to a large number of studies on sentiment analysis related to the Covid-19 period, and the word "polarity", which is used to express sentiment polarity, are observed. There are 281.100 words in the summaries of the relevant studies. These words also appear in artificial intelligence techniques and areas of use of sentiment analysis, like keywords.

Table 8. Abstract Part Word Frequency of Sentiment Analysis Studies

Word	Frequency	%
sentiment	9341	3,67
analysis	5828	2,29
data	2537	1,00
model	2458	0,97
social	2008	0,79
learning	1761	0,69
information	1759	0,69
text	1580	0,62

datasets	1537	0,60
opinions	1518	0,60
classification	1515	0,60
media	1319	0,52
tweets	1152	0,45
Twitter	1059	0,42
language	1036	0,41
negative	970	0,38
machine	956	0,38
network	951	0,37
positive	948	0,37
words	935	0,37
online	823	0,32
deep	792	0,31
polarity	783	0,31
public	752	0,30
neural	742	0,29

The word cloud of the summary sections of sentiment analysis studies is shown in Figure 8.

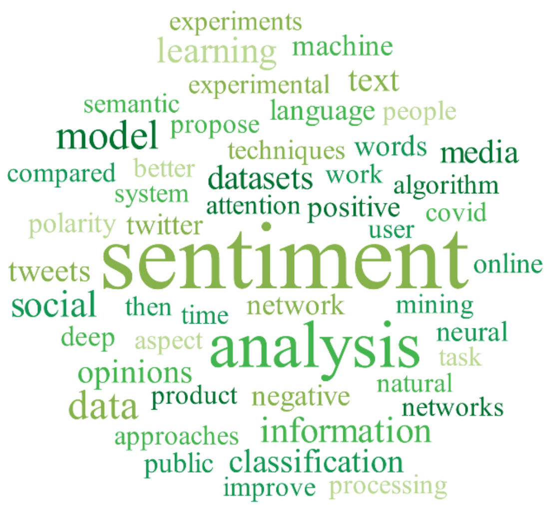

Figure 8. Word Cloud of Abstracts

To identify service quality studies using sentiment analysis, 23 articles were obtained as a result of the search. As shown in Figure 9, these studies were conducted between the years 2016-2022. While sentiment analysis studies began in 2008, the use of sentiment analysis in service quality started in 2016. It is observed that the use of sentiment analysis in service quality has increased along with the increase in sentiment analysis studies in the years 2021-2022. It can be seen that the use of sentiment analysis in service quality is still very new. Service quality is used in many sectors, especially in the private sector, and its importance is increasing in a competitive environment. The fact that the number of studies on the use of sentiment analysis in this area is small gives researchers opportunities in this field.

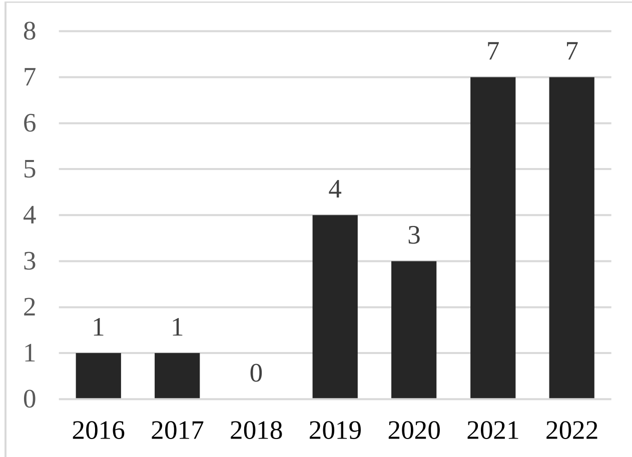

Figure 9. Graph of Service Quality Studies Using Sentiment Analysis by Year

In sentiment analysis studies, fields such as computer, artificial intelligence, information systems, and computer systems are more prominent, while in studies on service quality using sentiment analysis, there are more studies in business and management disciplines. The distribution of these disciplines by discipline is shown in Figure 10.

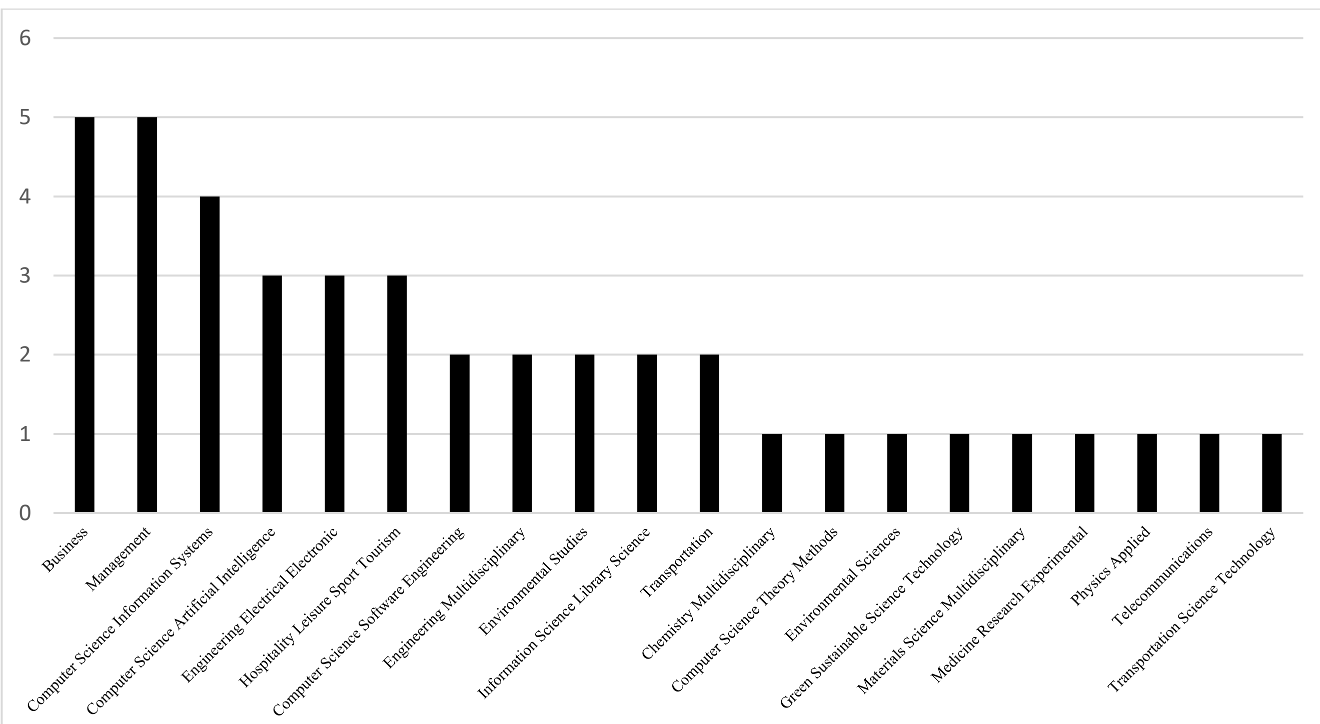

Figure 11. Discipline Distribution of Service Quality Studies Using Sentiment Analysis

The citation topics of the relevant articles were identified as management, information engineering, economics, mass transportation, entertainment, and tourism. Table 9 lists the articles that discuss service quality using sentiment analysis. The relevant articles received an average of 9.8 citations, while eight articles received no citations. The study by Liang and colleagues that received the most citations evaluated the comments on paid and free mobile applications in terms of product and service quality using sentiment analysis. They stated that the applications with a high service quality evaluation according to sentiment analysis are more effective in sales rankings [26]. Martin-Domingo et al. [27] analyzed Twitter data using sentiment analysis to measure airport service quality. They measured service quality by analyzing tweets containing important words and words with similar meanings related to aviation activities. They stated that this method provided a wider and more qualitative data set than traditional techniques.

Gitto and Mancuso [28], in their study stating that business methods are not sufficient for measuring airport service quality, aimed to evaluate customers' perception of airport service quality by collecting user comments from airline blogs to overcome this deficiency. Yu and Zhang [29] analyzed 814 reviews of 78 restaurants using sentiment analysis to identify the effect of emotions in online reviews on the quality of the food experience. They argued that this innovative method would open new dimensions for tourism research. Jain et al. [30]. used sentiment analysis techniques to predict customer recommendation decisions from online reviews in their study, highlighting the importance of customer reviews as a data source for performance measurement.

Rasool and Pathina [31] examined 1,777 reviews on the Trip Advisor application using sentiment analysis to investigate the change in customer perception of service quality in the airline industry, rather than relying on survey-based models. They claimed that user reviews could be used in interactive marketing, were relevant to dimensions of airline service quality, and reflected the satisfaction and general views of travelers in their interactions with the airline.
Tokarchuk et al. [32] used sentiment analysis to examine reviews on the Trip Advisor application for Berlin from 2013 to 2019 and developed an emotional index for the city's transport capacity.

Author	**Article Title**	**Number of Citation**	**Year of Publication**
Liang, TP; Li, X; Yang, CT; Wang, M	What is Consumer Reviews Affects the Sales of Mobile Apps: A Multifacet Sentiment Analysis Approach	80	2016
Martin-Domingo, L; Martin, JC; Mandsberg, G	Social media as a resource for sentiment analysis of Airport Service Quality (ASQ)	46	2019
Gitto, S; Mancuso, P	Improving airport services using sentiment analysis of the websites	37	2017
Yu, CE; Zhang, XY	The embedded feelings in local gastronomy: sentiment analysis of online reviews	17	2020
Jain, PK; Quamer, W; Pamula, R; Saravanan, V	SpSAN: Sparse self-attentive network-based aspect-aware model for sentiment analysis	11	2021
Rasool, G; Pathania, A	Reading between the lines: untwining online user-generated content using sentiment analysis	7	2021
Tokarchuk, O; Barr, JC; Cozzio, C	How much is too much? Estimating tourism carrying capacity in an urban context using sentiment analysis	7	2022
Zhou, G; Liao, CL	Dynamic Measurement and Evaluation of Hotel Customer Satisfaction Through Sentiment Analysis on Online Reviews	7	2021
Wang, Z; Wang, L; Ji, Y; Zuo, LL; Qu, SJ	A novel data-driven weighted sentiment analysis based on information entropy for perceived satisfaction	3	2022
Agarwal, S	Deep Learning-based Sentiment Analysis: Establishing Customer Dimension as the Lifeblood of Business Management	3	2022
Ho, SY; Choi, KW; Yang, F	Harnessing Aspect-Based Sentiment Analysis: How Are Tweets Associated with Forecast Accuracy?	2	2019
Ahmed, AZ; Rodriguez-Diaz, M	Significant Labels in Sentiment Analysis of Online Customer Reviews of Airlines	2	2020

Anitsal, MM; Anitsal, I; Anitsal, S	Is your business sustainable? Sentiment analysis of air passengers of the top 10 US-based airlines	2	2019
Chen, YY; Zhong, YM; Yu, SM; Xiao, Y; Chen, SN	Exploring Bidirectional Performance of Hotel Attributes through Online Reviews Based on Sentiment Analysis and Kano-IPA Model	2	2022
Shah, AM; Yan, XB; Tariq, S; Shah, SAA	Tracking patients' healthcare experiences during the COVID-19 outbreak: Topic modeling and sentiment analysis of doctor reviews	1	2021
Chalupa, S; Petricek, M; Chadt, K	Improving Service Quality Using Text Mining and Sentiment Analysis of Online Reviews	0	2021
Saputro, B; Hidayanto, AN; Abidin, Z; Paoprasert, N	Measuring service quality in the telecommunications industry from customer reviews using sentiment analysis: a case study in PT XL Axiata	0	2021
Zheng, X; Chen, W; Zhou, HJ; Li, Z; Zhang, TF; Yuan, Q	Emoji-Integrated Polyseme Probabilistic Analysis Model: Sentiment Analysis of Short Review Texts on Library Service Quality	0	2022
Chen, W; Zheng, X; Zhou, HJ; Li, Z	Evaluation of Logistics Service Quality: Sentiment Analysis of Comment Text Based on Multi-Level Graph Neural Network	0	2021
Ceyhan, M; Orhan, Z; Karras, D	Sentiment Analysis of Hospital Service Satisfaction	0	2020
Li, LY; Mao, YJ; Wang, Y; Ma, ZH	How has airport service quality changed in the context of COVID-19: A data-driven crowdsourcing approach based on sentiment analysis	0	2022
Mishra, DN; Panda, RK	Decoding customer experiences in rail transport service: application of hybrid sentiment analysis	0	2022
Ghosal, S; Jain, A	Weighted aspect-based sentiment analysis using extended OWA operators and Word2Vec for tourism	0	2022

Gang and Chenglin [33] suggest a framework for measuring and evaluating customer satisfaction from online reviews in hotels, noting that the academic community has paid attention to the measurement and evaluation of online reviews in recent years. In this framework, after obtaining relevant reviews, they recommend sentence processing and selection from the perspective of managers, identifying high-frequency words and topics, and extracting emotional intensity based on these. They aim to measure customer satisfaction with this emotional calculation.

Wang et al. [34] used sentiment analysis to analyze customer reviews collected online in their studies to analyze the perceived satisfaction of customers to prevent customer loss and a decrease in sales volume. They state that competitive analysis can be carried out by comparing the results with those of similar products and that the satisfaction result can become more detailed. In his study, Agarwal [35] emphasizes the importance of evaluating customer opinions in determining customer expectations for products and services for a profitable business. He argues that increasing customer satisfaction will increase brand and business demand and popularity. He states that it is necessary to examine customer experiences on social media, blogs, and review sites to understand the customer's perspective. He claims that sentiment analysis helps extract customer feedback and analyze the emotional tone of the customer, thus helping to understand how customers feel about a product or service.

When the first ten articles on service quality that mention sentiment analysis are examined, it is seen that opinions are collected from social media, websites, or blogs and analyzed using sentiment analysis techniques. Researchers have demonstrated the benefits and advantages of this method over traditional methods for more profitable businesses, more competitive organizations, and sustainable activities. It is common for researchers to track the number of citations their work receives, as this can be an indicator of the impact and influence of their research. The top ten authors by several citations in the field of service quality with sentiment analysis could be determined by looking at the citation data for the relevant articles. This list could be useful for identifying leading researchers in the field and understanding the contributions they have made to the research. However, it is important to note that the number of citations alone does not necessarily reflect the quality or significance of a researcher's work, and other factors such as the relevance and originality of their research should also be considered.

Table 2. Top Ten Authors by Number of Citations

Author	Number of Articles	Number of Citations
Li, Xin	1	80
Liang, Ting-Peng	1	80
Wang, Mengyue	1	80
Yang, Chin-Tsung	1	80
Carlos Martin, Juan	1	46
Mandsberg, Glen	1	46
Martin-Domingo, Luis	1	46
Gitto, Simone	1	37
Mancuso, Paolo	1	37
Yu, Chung-En	1	17

When the relevant articles are analyzed by country, it is seen that publications were made in 14 different countries. Table 11 shows the ranking of countries according to their total link power.Eight of the 14 countries have citation network connections with each other, while six do not have citation connections. There are no connections between the Czech Republic, Thailand, Austria, Australia, Albania, and Indonesia.

Table 11. Most Influential Countries Table

Country	Number of Publications	Number of Citations	Total Link Strength
USA	5	93	4
India	5	21	4
Italy	2	44	4
Denmark	1	46	3
Spain	2	48	3
Türkiye	1	46	3
PRC	8	110	2
Taiwan	1	80	1
Albania	1	0	0
Australia	1	2	0
Austria	1	17	0
Czech Republic	1	0	0
Thailand	1	0	0
Indonesia	1	0	0

Tablo 3. List of Journals with the Highest Link Strength

Source	Number of Publications	Number of Citations	Total Link Strength
Journal of Air Transport Management	2	46	2
Tourism Management Perspectives	1	37	2
Journal of Research in Interactive Marketing	1	7	2
International Journal of Electronic Commerce	1	80	1
Applied Sciences-Basel	1	2	1
Journal of Hospitality and Tourism Technology	1	17	0

Journal of Ambient Intelligence and Humanized Computing	1	11	0
Journal of Organizational and End User Computing	1	7	0
Tourism Management	1	7	0
Global Business Review	1	3	0
Journal of Retailing and Consumer Services	1	3	0

The lack of citation connections between journals is the reason why their total link power is zero or low. Only the Tourism Management Perspectives, Journal of Air Transport Management and Journal of Research in Interactive Marketing journals have citation connections between them. There are no connections between the other journals.

Tablo 4. Table of Title Word Frequencies

Word	Frequency	%
analysis	23	11,44
sentiment	22	10,95
service	8	3,98
reviews	7	3,48
online	6	2,99
quality	6	2,99
customer	5	2,49
airport	3	1,49
model	3	1,49
satisfaction	3	1,49

The table of keyword frequencies for the 23 relevant articles was found using the MAXQDA 2022 program, as shown in Table 13. Upon examination of this table of word frequencies, it was determined that researchers used online customer opinions in their studies on airport service quality by focusing on the keyword’s 'service', 'opinion', 'quality', and 'airport'.

Table 5. Abstract Word Frequency

Word	Frequency	%
sentiment	55	2,12
analysis	51	1,97
customer	48	1,85
service	47	1,81
quality	40	1,54
reviews	37	1,43
satisfaction	24	0,93
online	23	0,89
airport	16	0,62
hotel	14	0,54
positive	14	0,54
results	13	0,50
airline	12	0,46

evaluation	12	0,46
attributes	11	0,42
information	11	0,42
methods	11	0,42
approach	10	0,39
negative	10	0,39
performance	10	0,39
rating	10	0,39
review	10	0,39
texts	10	0,39
words	10	0,39
covid	9	0,35

The abstract sections of the relevant studies have word frequencies as shown in Table 14. While the keywords related to artificial intelligence techniques stand out in sentiment analysis studies, here we see keywords such as customer satisfaction, customer opinions, and various service sectors. This shows that the focus of the studies is on the customer and that the service sector is included. The word cloud of the summary sections of the relevant studies is shown in Figure 12.

Figure 12. Word Cloud of Abstract Section

4. CONCLUSIONS

In recent years, people's lifestyles have become increasingly digitalized, and as a result, they tend to express their feelings in written form on social media platforms, websites, blogs, and forums. This has led to a change like research in the social sciences, as data collection methods have also become digitalized. Sentiment analysis, which was born and developed within computer science, has increasingly been used in the social sciences as a result of this change. In this study, 2538 articles and 7329 authors were analyzed for the search word sentiment analysis. When the distribution of these articles by years is analyzed, the number of articles has increased in recent years. In the analysis, important studies in this field were identified. The articles that stand out in the analysis will be a guide for researchers who want to conduct studies related to sentiment analysis. In addition, 23 articles on the use of emotion analysis technique in the field of service quality were analyzed. The new use of sentiment analysis technique in the field of service quality gives researchers the opportunity to work in this field.

However, a bibliometric analysis and content analysis of sentiment analysis studies shows that they have not yet reached sufficient maturity. The number of studies in this area has increased in recent years, and it is expected to continue to increase as the use of sentiment analysis expands to different disciplines. Service quality studies began in the 1960s using classical data collection methods, and various scales have been developed for this purpose. These scales were first digitalized in data collection methods. Techniques such as natural language processing, text mining, and sentiment analysis are replacing these classical methods. A bibliometric analysis of sentiment analysis in the context of service quality shows that studies in this area began in 2016. The number of studies in this area is still very small, and researchers from various disciplines in the social sciences are using sentiment analysis techniques to measure service quality in their fields.

However, there is not yet a network of researchers in this area. The increasing number of studies in recent years and the development of sentiment analysis techniques show that the use of sentiment analysis in service quality will continue to grow. In this study, the place of sentiment analysis in the literature was determined, and the current state of the use of sentiment analysis in service quality studies was examined. As a result of the study, it was determined that sentiment analysis can be used effectively in service quality studies and that there is a need for more interdisciplinary studies in this area.

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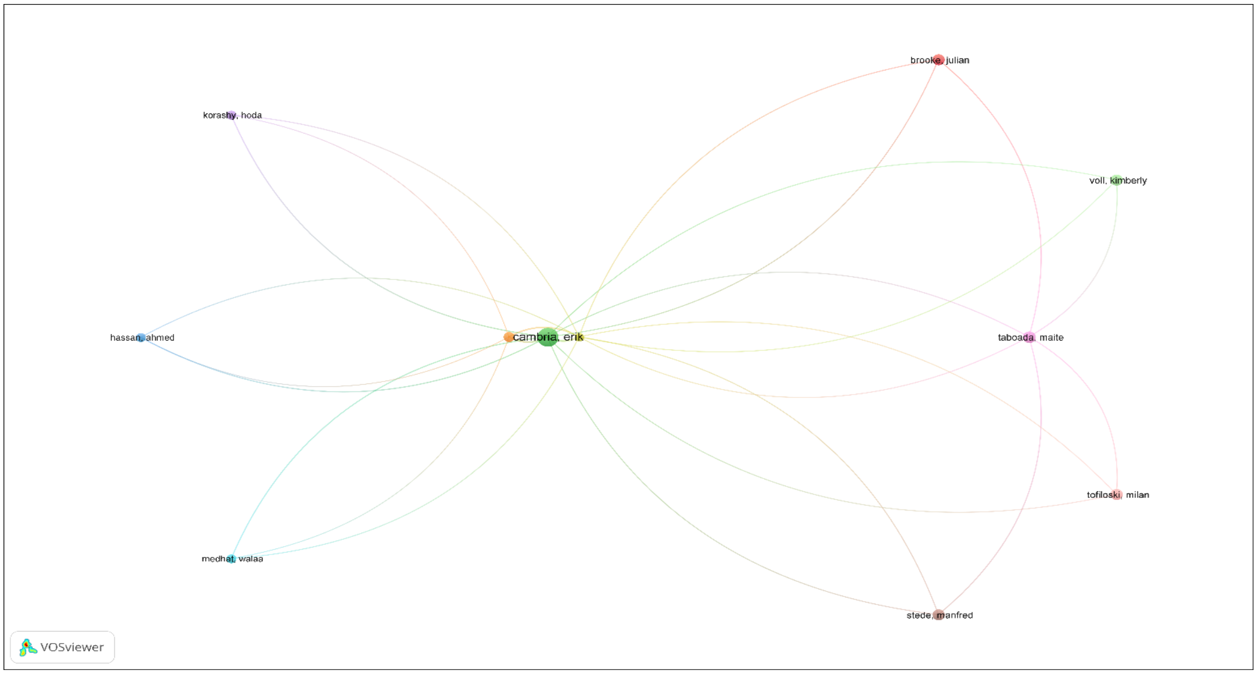
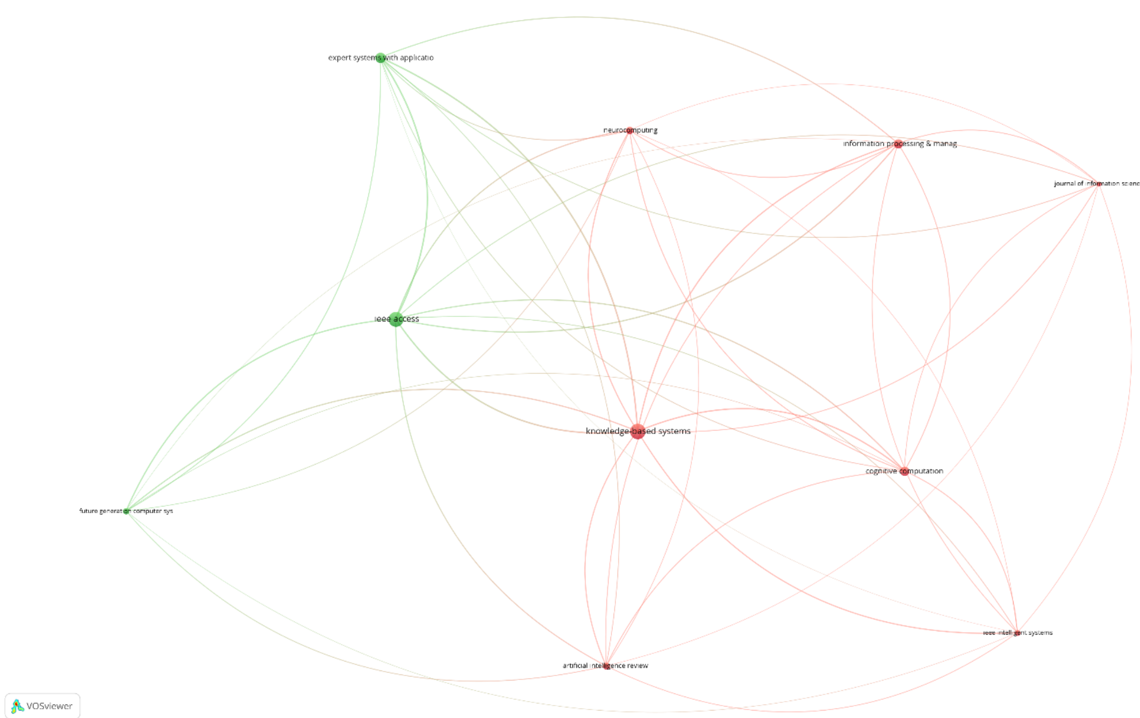
Appendices

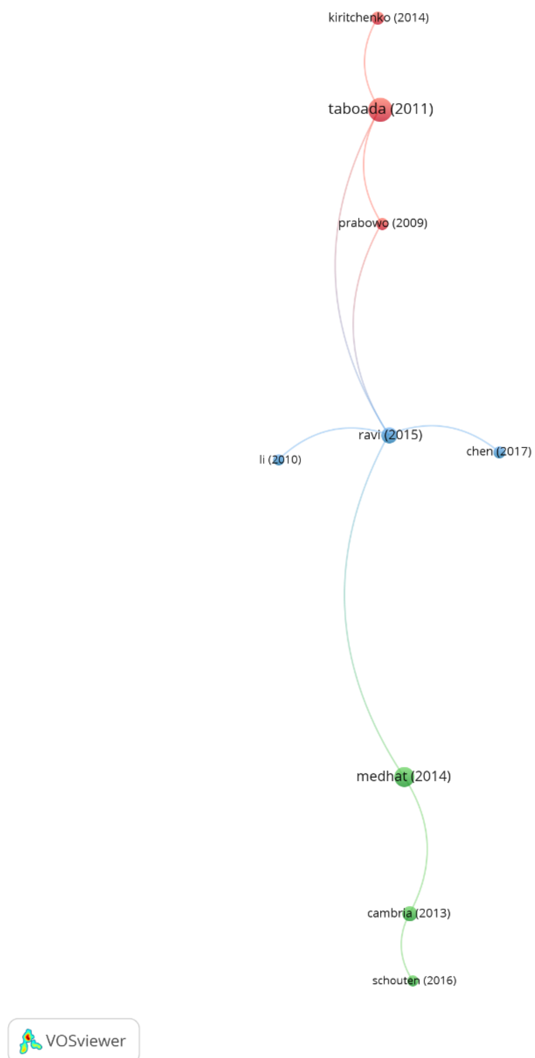
Appendix A.



Appendix B.



Appendix A.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