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Review

Artificial Intelligence and Sentiment Analysis: A Review in Competitive Research

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Abstract: As part of a business strategy, effective competitive research helps businesses outperform their competitors and attract loyal consumers. To perform competitive research, sentiment analysis may be used to assess interest in certain themes, uncover market conditions, and study competitors. Artificial intelligence (AI) has improved the performance of multiple areas, particularly sentiment analysis. Using AI, sentiment analysis is the process of recognizing emotions expressed in text. AI comprehends the tone of a statement, as opposed to merely recognizing whether particular words within a group of text have a negative or positive connotation. This article reviews papers (2012–2022) that discuss how competitive market research identifies and compares major market measurements that help distinguish the services and goods of the competitors. AI-powered sentiment analysis can be used to learn what the competitors' customers think of them across all aspects of the businesses.

Keywords: artificial intelligence; sentiment analysis; competitive research

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1. Introduction

The long-term viability of businesses is largely dependent on their capacity to satisfy client requirements. In reality, the purpose of customer satisfaction is to develop brand value, which is a crucial aspect of a company's long-term viability [1]. As a result, several businesses spend astronomical sums on marketing research to obtain knowledge about customer preferences and wants. To build effective branding and positioning strategies, it is essential to comprehend how customers perceive the items they purchase based on these data. Today's commercial environment is far more complicated, with other actors' interests creating a dynamic setting [2]. This dynamic of the contemporary business environment makes organizations more reliant on a system for early change detection to react properly [3]. However, businesses need resources and time to adapt to a changing environment, in which they will face risks and dangers that threaten their security and viability. In pursuit of common aims and interests, firms should build complementary, synergistic, interactive, and goal-oriented actions [4].

In light of this, competitive research—also known as competitor analysis—is a method for determining how well the firm and its goods or services are doing in comparison to other organizations providing comparable products or services in the market. Understanding how customers feel about their rivals and why is one of the most crucial components of a successful strategic competitive study. This will assist in determining the true strengths and limits across various business factors. This entails performing market research to obtain information for commercial purposes. Using text analytics to undertake sentiment analysis is one of the finest approaches to achieving this objective.

Marketers utilize sentiment analysis to better comprehend their consumers via what is referred to as the voice of the customer. Understanding client sentiments, beliefs, and motives is essential for more effective advertising to specific groups. Sentiment analysis is the process of finding, evaluating, and categorizing as negative (-1), neutral (0), or positive (+1) the emotions expressed by individuals in any text data kind. It is a subtype of affective computing that seeks to recognize, evaluate, and categorize subjective information from the source material, such as emotions. Although its popularity has increased in the most recent decade, sentiment analysis dates back to the late 1990s [5]. This enables marketers to make more informed decisions on the methods, channels, and creativity they use to communicate with customers. Although sentiment research may help marketers understand the consumers, it can also help learn what the rivals' customers think of them across various company factors, such as price, customer service, value, features, goods, mobile apps, etc. Comparing how a brand's goods or services are viewed by customers to those of its rivals, sentiment analysis presents a report. Brands may utilize this useful information to position themselves favorably in comparison to their competition.

Lexicon-based techniques and artificial intelligence (AI) or machine learning-based approaches may be used to categorize sentiment analysis methodologies [6,7]. Sentiment analysis powered by AI is becoming a vital tool for businesses. It aids in the gaining of an insight into clients' thoughts. Additionally, it is practical for comprehending the feelings and ideas of workers. However, it is mostly used to understand client feedback, the severity of a service case, social media references, etc. It may be argued that sentiment analysis will be employed in the not-too-distant future to delve deeper into human emotions. It will aid computers in better comprehending the feelings conveyed in communications, remarks, and feedback. This will enable businesses to tailor their answers better.

To enable new researchers to keep up with the area's development and to provide guidance for enhancing the quality of future research, the goal of this study is to review the literature on AI-based sentiment analysis. The present study is organized as follows: The second part presents the study background. The third portion details the research methodology used to locate, sort through, and choose the literature. The literature on AI-based sentiment analysis is discussed in the fourth part. Some of the most significant issues are highlighted, the most popular articles are provided, and their application is explored. The study's result is provided in the last part.

2. Background of the Study

Companies should concentrate on their clients and invest a lot of money in research to create a successful marketing plan, from the competition and feedback analysis to product fit in emerging markets. The importance of data in creating strategies, tools, and tactics to make a firm stand out is therefore clear. However, any effort to categorize, interpret, and even monetize the enormous quantity of accessible unstructured data appears to be an impossibility [8]. To thrive, businesses need to understand the wants, feelings, and behaviors of consumers [9]. The connected issues are resolved by sentiment analysis. It contributes significantly to competitive research. Getting customers to use any organization's services is the most crucial aspect of any company. Marketing the company is one of the most intriguing ways to obtain consumers. A novel marketing strategy is applied in this day and age. This marketing tactic appeals to clients by using human emotions. In sentiment analysis, a customer's feelings influence his decision to purchase a certain product. Sentiment analysis and machine learning approaches may improve a brand's performance and provide satisfying customer experiences [10]. The following parts present the background of the three major components of this review.

2.1. Competitive Research

Businesses should routinely and methodically analyze and assess their rivals' strategies, goods, and services in the present dynamic and complex business environment to stay competitive [11,12]. Businesses should monitor and analyze their rivals' social media platforms as well as their own since businesses as a whole are utilizing social media to communicate with both current and future clients. According to Dey et al.'s [12] study, social media also offers a chance to compare client behaviors towards rival businesses in addition to providing information about competitors. For businesses to obtain quick feedback from consumers and provide analytical reports that aid in customer acquisition and retention, social media competitive research has grown to be a vital talent [13–15]. For example, social data analysis in social media has already been the subject of much research [16,17]. Yanga et al. [16] suggested a business decision-making system based on social media analytics since they found it challenging to convert social media data into business information. To aid in managing the food supply chain, Singh et al. [18] advocated using text mining and hierarchical clustering in social media analysis. A theoretical model was developed by Ramanathan et al. [19] to help merchants use data from social media sites to better serve their consumers. Support vector machines were used by Ramasamy et al. [20] to categorize Twitter data into negative, neutral, and positive attitudes to enhance corporate decision making. Burdisso et al. [21] presented a supervised text categorization strategy to solve issues with early risk assessment. With the rise in online social media, consumers now have a rare but significant voice for publicly expressing their views on goods and services. Delivering fresh perspectives on customer relationships and brand management, this revolutionizes how consumers and businesses engage. Sentiment analysis is used to analyze, collect, and evaluate the impact of consumer views.

2.2. Sentiment Analysis

An approach for discovering ambiguity in words, views, etc., is sentiment analysis [22]. Sentiment analysis tells how a representative and a user feel about a certain issue. Opinions or feelings are reflected in a writer's choice of tone or expressive style. Numerous algorithms have been introduced lately to analyze, predict, and evaluate feelings from text data, such as product or customer reviews. Polarity recognition is a process that may be immensely aided by sentiment analysis. In addition to these concerns, it has problems with spam and false data, domain dependency, negation, the burden of natural language processing (NLP), bipolar terminology, and a wide vocabulary. Preprocessing elements are needed for sentiment analysis to organize the text and extract information that text-mining heuristics and machine learning algorithms may use later [23]. The procedure of preparing and cleaning the text for categorization is known as preprocessing the data [24]. Preprocessing's goal is to classify a group of characters from a text stream, switching between states based on the presence of certain letters. Arbitrary text sequences may be handled well by carefully considering the set of characters—punctuation, emojis, emoticons, and white spaces [23]. Preprocessing is required before unstructured data are fed to any AI system since computers, unlike humans, cannot comprehend them. The findings of research by Nhlabano and Lutu [25] indicated that text preprocessing strategies improve the sentiment analysis accuracy of the final algorithms.

To enhance the efficacy of the data-mining process, it is important to address the issues outlined before [26]. The research by Mangold et al. [27] demonstrated that semantic sentence analysis may enhance precision, consistency, and methodology. Text-based consumer review data on digital platforms have increased tremendously. Various strategies have been used by marketing researchers to examine text reviews. Kanakaraj et al. [28] demonstrated that the improved NLP method, in which the emotion taxonomy is improved by incorporating word senses and reference senses into vector features and employing ensemble methods for classification, improved the accuracy of predictions.

NLP may examine, highlight, and extract meaning from text and voice using machine learning and algorithms [29]. In its simplest form, this could involve using an AI framework to scan text to identify specific words or phrases. However, in its more advanced applications, it enables computers to recognize the emotion of the speaker—sometimes superior to a human. Utilizing sophisticated AI tools in an inventive manner might be a successful method for sentiment research.

2.3. AI

AI refers to the development and theory of computer systems that are capable of performing activities that ordinarily require human intellect, such as visual perception, voice recognition, decision making, and language translation. The ideas can be used in a variety of business sectors, including decision support, new service and product development, capacities, etc. The AI strategies use deep learning and machine learning.

Deep learning is used to analyze a vast array of practical applications. Classification tasks need labeling datasets since they may be used to detect data patterns. When using a labeling dataset, the user should apply his or her prior knowledge to the labeled set. This allows the neural network and the system to relate the data to their respective labels. Here, supervised learning is occurring [30].

There is now cutting-edge technology that combines the finest of mathematics, statistics, and AI thanks to the development of machine learning [31]. The fundamental idea of AI and machine learning technologies is that engineers should not be limited to developing programs. Therefore, it should be feasible to create a computer that can train itself how to write programs [32]. The software should be "intelligent" in the sense that it is capable of learning from past data and interactions. This is essential. As a consequence of AI, the software may now develop its programs and apply what it has learned to propose proactive future solutions. Utilizing the huge volumes of data they have acquired, firms employ machine learning to provide actionable forecasts for executives.

3. Research Methodology

3.1. Review Planning

When the subject under investigation has not been thoroughly researched by others, scoping reviews offer a systematic approach to a broad topic and identify research gaps. Frequently, systematic reviews will follow a scoping review to assess the caliber and rigor of the evidence available [8,9]. This scoping study set out to assess the level of AI-based sentiment analysis in contemporary competitive research. All current relevant literature was studied for our investigation with the greatest seriousness. The Scopus database, structured research questions (RQs), and information gathering and analysis techniques were all heavily used in the review process. To give a thorough assessment of the research subjects, a particular subset of the mandatory reporting elements for scoping reviews was selected. These are the specifics of the RQs:

RQ1: How is the current state of research?

RQ2: What is the development of the major AI-based sentiment analysis approaches?

RQ3: What are the difficulties and prospects of AI-based sentiment analysis in competitive research?

3.2. Research Strategy

A literature search from 2012 to 2022 was conducted to analyze AI-based sentiment analysis applications, approaches, and futures. The sources from Scopus were looked at throughout the investigation. Relevant databases were evaluated to ensure the accuracy of the information supplied here. However, not all of the excellent works of literature were included in the search criteria for a variety of reasons. A total of 133 Scopus results were examined up to December 26th, 2022. A total of 43 were deemed significant. The study domain and research subjects affected how the search string was created. To choose relevant papers for the review, inclusion and exclusion criteria were devised and key terminology was identified (see Table 1 for more detail). Articles were chosen using the PRISMA diagram as a guide (Figure 1).

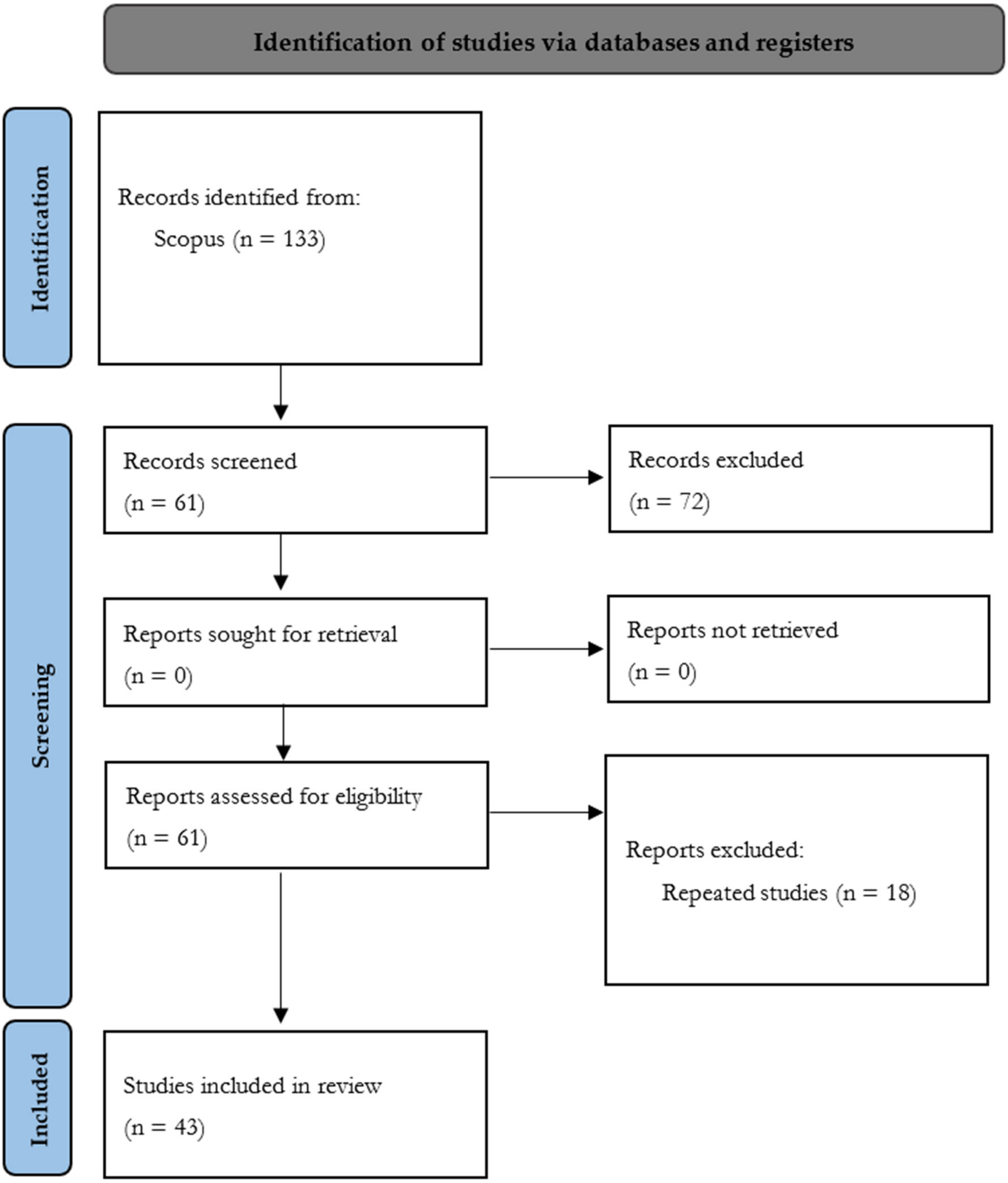

Figure 1. PRISMA flowchart illustrating the method for selecting papers for scoping review.

Table 1. Search Strategy.

Key Terminology	Inclusion Criteria	Exclusion Criteria
"AI" AND "Sentiment Analysis", AND "Competitive" OR "Business" OR "Market" OR "Customer" OR "Product" OR "Service".	1. The publication of research may occur at any time between 2012 and 2022.	1. The deletion of articles in press.

Table 1. *Cont.*

Key Terminology	Inclusion Criteria	Exclusion Criteria
"Artificial Intelligence" AND "Sentiment Analysis", AND "Competitive" OR "Business" OR "Market" OR "Customer" OR "Product" OR "Service".		
"Machine Learning" AND "Sentiment Analysis", AND "Competitive" OR "Business" OR "Market" OR "Customer" OR "Product" OR "Service".	2. The scope of the study is limited to the journal.	2. Articles not written in English
"Deep Learning" AND "Sentiment Analysis", AND "Competitive" OR "Business" OR "Market" OR "Customer" OR "Product" OR "Service".		
"Artificial Intelligence" AND "Sentiment Analysis"		
"AI" AND "Sentiment Analysis"		

4. Results and Discussion

The answers to the RQs from the earlier scoping review are shown here. The use of AI-based sentiment analysis in competitive research seems to have greatly advanced as a result of this work. This section outlines the history, current status, difficulties, and tendencies of AI-based sentiment analysis. Included here are the answers to the RQs from the earlier scoping review. This study seems to improve competitive research's use of AI-based sentiment analysis.

Selection Results

This search produced 133 items, 90 of which were examined. This scoping review consists of 43 publications. The selected publications and an explanation of the overall classification results are presented below. The review database, which is mostly Scopus, places restrictions on the review process.

RQ1: How is the current state of research?

The descriptive information that has been acquired from the many papers that are published each year, including topic categories, keyword density, document type, and author country distribution, is examined in this scoping research. The examination of research articles on AI-based sentiment analysis in indicated applications that were published between 2012 and 2022 comes to a close with this scoping analysis.

The document type of the papers is seen in Figure 2. Articles make up 86% of all publications; the remaining 14% are reviews and editorials. It can be a sign that this field is seeing growth. Future growth in the number of review articles is assumed.

The number of articles produced for each topic area from 2012 to 2022 is shown in Figure 3. The primary topic is Computer Science (31 articles). Engineering (17 articles), Business, Management and Accounting (8 articles), Mathematics (7 articles), Social Sciences (6 articles), Decision Sciences (5 articles), Materials Science (5 articles), etc., are also addressed in the collection. Because AI is a broad field of Computer Science, and sentiment analysis is related to it, it is apparent that Computer Science is the main subject area.

The number of publications released each year between 2012 and 2022 is shown in Figure 4. No documents were available from 2012 to 2017. The following shows how publishing dates have changed throughout time: one paper (about 2.32% of the total) was published in 2017, none in 2018, five papers (about 11.63%) in 2019, nine papers (20.93%) in 2020, twelve papers (about 27.91%) in 2021, and sixteen papers (about 37.21%) in 2022. Moreover, it is clear that from 2019 to 2022, the number of articles rose annually. It could be associated with the expansion of artificial intelligence (AI) and sentiment analysis in business studies.

Figure 2. Number of papers based on document type.

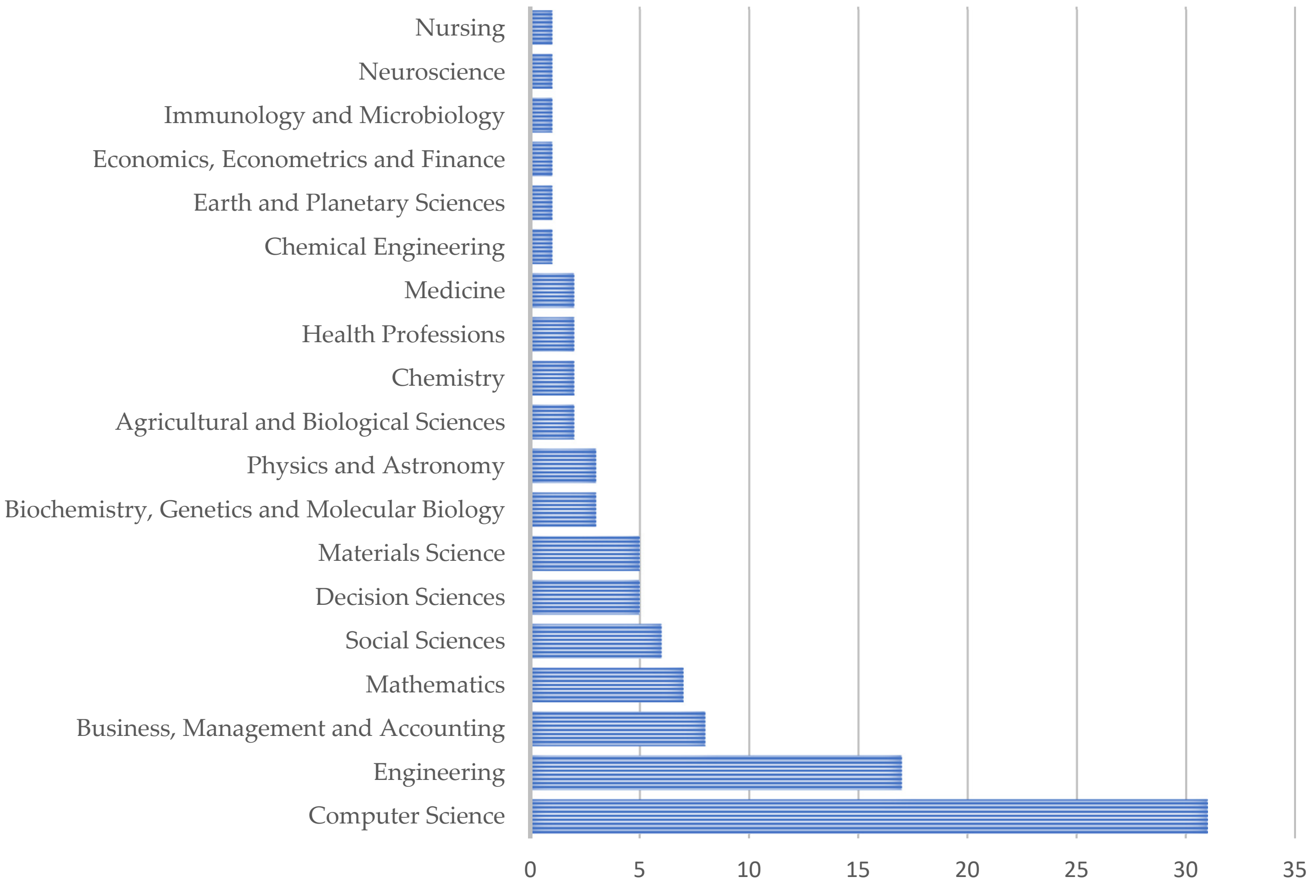

Figure 3. The number of papers published based on subject area between 2012 and 2022.

The link between the keywords of the papers selected for the scoping literature review is shown in Figure 5. The study revealed that the following terms were commonly used: sentiment analysis, deep learning, machine learning, artificial intelligence, learning algorithms, natural language processing, social networking (online), and many more. Table 2 summarizes the usage of the keywords.

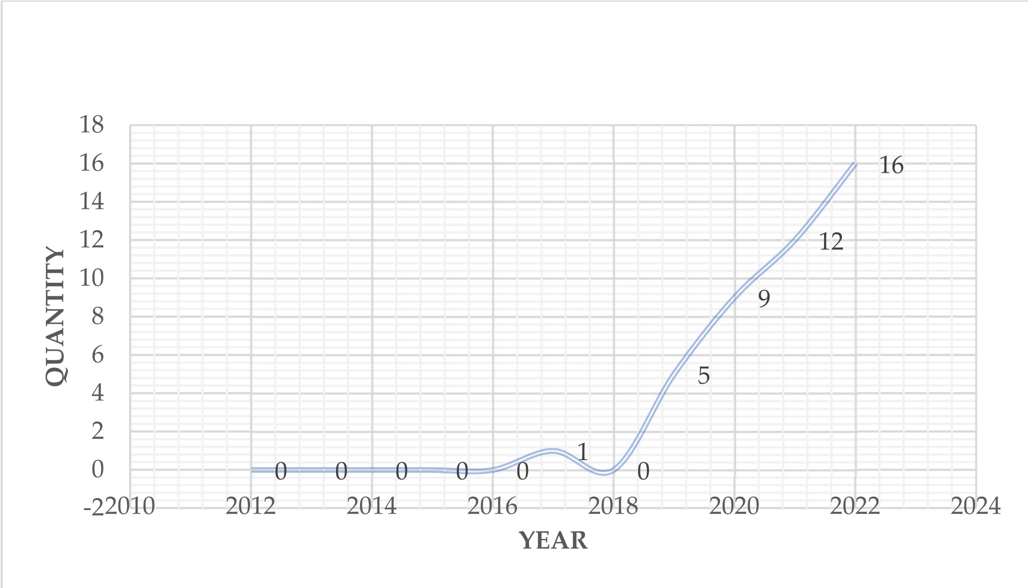

Figure 4. The number of annual publications between 2012 and 2022.

Figure 5. Keywords usage cloud (created by www.wordclouds.com).

The proportion of authors by nationality is shown in Figure 6. India has the most writers with 19. China has seven authors, Malaysia has six, Saudi Arabia has six, Taiwan has five, the United States has five, etc.

Table 3 lists the ten most cited papers between 2012 and 2022. Some of the most often referenced areas of papers include sentiment analysis using deep learning and sentiment lexicon, AI for social network analysis of COVID-19 emotions, consumer sentiment analysis based on machine learning, and the study of face sentiment using AI approaches.

Table 2. Keywords' Employment.

Keyword (s)	NO.
Sentiment Analysis	32
Deep Learning	19
Machine Learning	16
Artificial Intelligence, Learning Algorithms	8
Natural Language Processing, Social Networking (online)	7
Data Mining, Feature Extraction	6
Convolutional Neural Network, Learning Systems	5
Article, Commerce, Convolutional, Neural Networks, Electronic Commerce, Human, Machine-learning, Social Aspects, Social Media, Twitter	4
COVID-19, Customer Satisfaction, Extraction, Long Short-term Memory, Neural Networks, Public Sentiments, Quality Control, Recurrent Neural Networks, Sales, Support Vector Machines	3
Algorithm, Algorithms, Artificial Intelligence Techniques, Attention Mechanisms, CNN, Commercial Phenomena, Convolutional Neural Networks (CNN), Customer Review, Data Mining And Machine Learning, E-commerce Websites, E-learning, Emotion Analysis, Financial Markets, Humans, LSTM, Large Dataset, Learning Approach, Learning Technology, Naive Bayes, Natural Language And Speech, Natural Languages, Natural Speech, Online Social Network, Pandemic, Pandemics, Product Reviews, Products And Services, Public Opinions, QoE, Recurrent Neural Network (RNN), Sensing, Sentimental Analysis, Telecommunication Services	2
AI And Risk, AI Technologies, API Crawler, Accuracy, Acoustic, Activation Analysis, Activation Functions, Algorithm And Analyse Of Algorithm, Algorithms And Analysis Of Algorithms, Analysis Algorithms, Analysis Of Algorithms, Analysis Strategies, Antennas, Area Of Interest, Artificial Intelligence (AI), Artificial Intelligence Of Things, Artificial Intelligence Technologies, Artificial Intelligence Tools, Arts Computing, Aspects, Attention, Attention Mechanism, Base Stations, Bat Algorithm, Bat Algorithm (BA), Beauty Products, Behavioral Research, Bert, Bi-directional, BiGRU, Bidirectional GRU, Big Data, Big Data Analytics, Bipolar Words, Brain, Business Application, Business Applications, Business Boosting, Business Decisions, Business Economy, Business Intelligence, Business Performance, CRISP-DM, Character Error Rate, Classification (of Information), Clustering And Classification, Colombia, Competition, Computer Vision, Consumer Reviews, Consumer Satisfactions, Convolution, Convolution Neural Network (cnn), Coronavirus, Coronavirus Disease 2019, Coronavirus Infection, Coronavirus Infections, Corporate Social Responsibilities (CSR), Corporate Social Responsibility, Cosmetics, Cost Effectiveness, Costs, Crisis, Crisis Management, Customer Reviews, Data Analytics, Data Augmentation, Data Collection, Data Fusion, Data Handling, Data Science, Decision Support System, Decision Support Systems, Deep Belief Network, Deep Belief Networks, Deep Learning (dl), Deep Neural Networks, Deep Reinforcement Learning, Delivery Of Health Care, Depression, Different Sizes, Digital Health, Distributed Machine Learning, E-commerce Domains, E-commerce Product Reviews, E-commerce Services, Economic Aspect, Economics, Electronic Trading, Elman Neural Network, Elman Neural Network (ENN), Embedding Models, Embeddings, Emoji, Emoticons & Emojis, Emotion, Emotion AI	1

Table 3. The most cited articles (2012–2022).

System	Year	Document Type	Cited by	Reference
Chinese e-commerce product review sentiment analysis using deep learning and sentiment lexicon	2020	Article	145	[33]
Implementation of AI to social network analysis of COVID-19 emotions	2020	Article	98	[34]
Customer sentiment analysis based on machine learning for suggesting buyers and stores based on customer reviews	2020	Article	44	[35]

Table 3. *Cont.*

System	Year	Document Type	Cited by	Reference
Analysis of facial sentiment using AI techniques	2020	Article	43	[36]
A sentiment analysis of online product evaluations using machine learning with a new term weighting and feature selection technique	2021	Article	37	[37]
Sentiment analysis and data extraction of halal products on Twitter using a stack of deep learning algorithms	2019	Article	33	[38]
A deep learning approach to sentiment analysis in Spanish for the improvement of services and products	2017	Article	32	[39]
Aspect-level sentiment analysis based on machine learning for Amazon items	2020	Article	28	[40]
Emotional AI-based sentiment analysis	2019	Review	27	[41]
Deep learning for social media sentiment research to improve stock market forecasting	2021	Article	21	[42]

RQ2: What is the development of the major AI-based sentiment analysis approaches?

Every business enterprise can make use of the vast and developing area of sentiment analysis of natural language texts to help them decide what services and products to provide [43]. Sentiment analysis is a task that uses information extraction and NLP to evaluate a huge number of documents to identify the writer's emotions expressed in negative or positive terms, interrogations, and appeals.

Researchers have employed machine learning approaches for a sufficient amount of time. Machine learning's accurate learning paradigm is why it has undoubtedly been among the most promising entity in the field of AI. Although machine learning approaches require learning from qualities, the attributes should be chosen by humans [44]. Even though several machine learning techniques may be used in various business domains, there is currently no most appropriate and universally agreed upon strategy. People in many organizations test one kind of strategy and then repeat it. There is no set procedure to follow when making business predictions. The search for any generic standard machine learning techniques for various commercial areas should thus go deep.

According to Sonosy et al. [45], gathering a sizable quantity of data from several sources is necessary for comprehending how business trends behave. Location-based social networks may provide a huge quantity of data that can be analyzed to understand business habits. To forecast business meetings, data are gathered. Using a spatial regression model and machine learning, predictions are made. To identify links between dataset elements for predicting business behavior, authors thoroughly examined spatial regression models and completed a thorough investigation. According to Singh et al. [46], emotional analysis is crucial to business intelligence because it helps to understand customer feedback and behavior, which improves prediction and decision making. They merged NLP with a machine learning strategy to do this. Machine learning techniques may be used to monitor business support systems, according to Chen et al. [47], to estimate performance metrics and sometimes to identify the reasons for performance decline. While it may not always be helpful for certain crucial business support systems, it may speed up troubleshooting and enable preparation for emergencies. To anticipate a system's health status an hour before an emergency with an average inaccuracy of 14 points and with sufficient time to spare for troubleshooting, they employed the random forest machine learning model. Ghiassi et al. [48] spoke on how social media statements on Twitter may provide businesses with useful input about their goods and brand. They focused on the difficulties associated with the particular Twitter language and the distribution of tweet emotion classes connected to brands. To classify Twitter's emotions about two different brands, they applied the SVM supervised learning model.

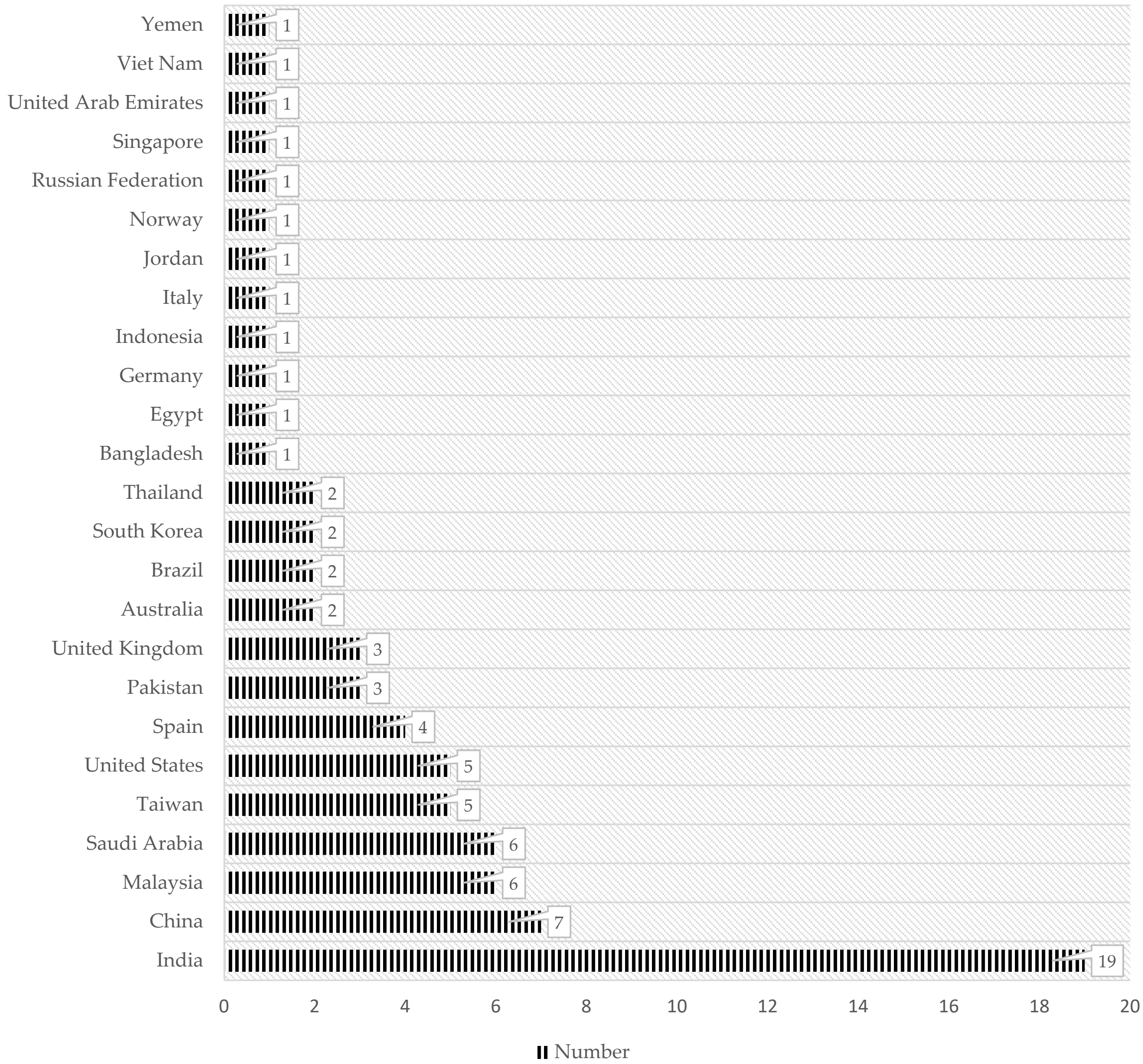

Figure 6. Country-by-country breakdown of writers.

The next phase was using a multilayer representational learning technique known as deep learning. These include several straightforward yet non-linear modules that translate a basic input into a more complex representation, enabling several levels of complexity to be learned. Deep learning approaches showed great performance across all applications in the area not long after the momentum in NLP continued to grow.

Techniques have been proposed by several scholars to solve issues with sentiment analysis as well as the mining and analysis of customer reviews. In this part, a comprehensive examination of earlier work is offered. A rapid, adaptable, all-inclusive method for sentiment analysis from the text that depicts people's sentiments in many languages was proposed by Giatsoglou et al. [49]. With the use of deep learning, the textbook is digested and assessed using word embedding and ConvLSTM architecture. Text-based consumer evaluation data on digital platforms has greatly increased. To assess text reviews, marketing professionals have used a variety of methodologies. The empirical trade-off between predictive and diagnostic abilities was examined by Alantari et al. [50]. They found that neural network-based machine learning algorithms provide the most accurate predictions. Topic models, however, are not well suited for making predictions, and neural network models are not well suited for making diagnoses.

Sentiment analysis looks at the specific product reviews that consumers have provided. Aspect-based sentiment analysis (ABSA) analyzes and categorizes the opinions expressed on the many elements of these opinions to provide decisive recommendations. This study explores the development of the ABSA model in Hindi reviews to extend the understanding of the submitted Hindi text [51].

Desai et al. [52] employed machine learning and NLP to extract the sentiments from the reviews in their dataset. They also used business intelligence (BI), namely Microsoft Power BI, to help companies that sell these products streamline their processes and improve customer satisfaction. Thanks to reviews written by consumers who have already bought the product, the two aforementioned assertions are related. The firms creating the items and prospective buyers should analyze and gain insights from such active feedback. This essay explores the advantages of business intelligence and sentiment analysis for clients and businesses. It provides a summary of how their goods or services performed on the market, customer happiness, and numerous use cases for producers and consumers. Devika et al. [53] compared several sentiment analysis approaches. Their research led to the conclusion that effective strategies are required to execute the categorization job.

RQ3: What are the difficulties and prospects of AI-based sentiment analysis in competitive research?

Although AI-driven sentiment analysis has many benefits, serious obstacles should be overcome. The problems listed below may be overcome to make sentiment analysis more effective and efficient so that it can be used in all situations. Even though there has been a lot of study in this area, certain things still require further analysis and research.

Future academics will face new strategic imperatives when semantic information and machine learning for deeper consumer insights are developed [54]. Algorithms for reasoning that are psychologically motivated and inspired by the brain would increase the predictability of customer behavior. Intelligent sentiment mining systems will be created using a combination of technical techniques and psychological theories addressing the cognitive and emotional demands of customers. In the future, improved sentiment categorization will be possible thanks to hybrid machine learning algorithms [55]. The use of AI in marketing will increase with the development of optimization models based on current marketing theories [56].

The complexity and precision of projected behavior are increased by the overt and covert usage of emotional expressions on social media. Linguistic patterns for deep learning may aid in the detection of sarcasm and enhance the prediction of emotion. Future researchers would benefit from the development of micro text and anaphora resolution for dealing with dynamic sentiment analysis [57]. Market acceptance of knowledge-based systems is increased by co-creation; thus, future researchers should work to develop cooperative market intelligence [58]. For big data sentiment analysis, future researchers should focus on high-inflection languages and consider emotive lexicons [49].

Using cutting-edge AI algorithms, sentiment analysis is now taking place all over the globe, while its full potential is yet unknown. Unsurprisingly, there are many service alternatives available for businesses interested in using these methods in the booming industry of sentiment analysis as a service. The investment will not immediately assist every business in every sector. However, sentiment analysis will probably be a crucial component of a great customer experience and engagement in the future. The value of new technology is not in the data acquired but in the use to which that data is put. The potential of AI is in utilizing tools to better understand the consumers and then taking appropriate action based on that knowledge, not in removing the need to do so.

5. Conclusions

One of the most important elements of good strategic competitive research is understanding the perceptions, and the reasons behind these, that consumers have of the competitors. This will help ascertain the actual strengths and weaknesses of various firm's components. This comprises conducting market research to obtain data for business uses. One of the best ways to accomplish this goal is to use text analytics to perform sentiment analysis. Sentiment analysis creates a report by comparing how consumers perceive a brand's products or services to those of its competitors. Brands may use these insightful data to distinguish themselves positively from the competition. AI-powered sentiment analysis is beginning to be used by enterprises as a key tool. It helps in obtaining an understanding of customers' perspectives. It is also helpful for an understanding of the thoughts and sentiments of employees. The majority of the time, it is utilized to understand customer reviews, the seriousness of a service problem, social media references, etc. It might be claimed that sentiment analysis will soon be used to probe deeper into people's feelings. It will help computers understand the emotions expressed in messages, comments, and feedback better. Businesses will be able to better personalize their responses as a result. This study aimed to examine the literature on AI-based sentiment analysis to help new researchers stay up to date with the progress of the field, and to give suggestions for improving the quality of future research. This review comprised works published between the years 2012 and 2022, and it looked at the status of AI-based sentiment analysis at the time, as well as its methodologies, difficulties, and prospects. The total number of articles on this subject that were taken into consideration for this evaluation was 43. Results indicate that this profession is becoming more academic with time. Though its full potential is yet unclear, sentiment analysis is currently being performed all over the world using cutting-edge AI algorithms. Unsurprisingly, burgeoning sentiment analysis as a service market offers a wide range of service possibilities for companies interested in using these techniques. Not all businesses in all industries will receive assistance right away from the investment. However, I am making a wager that, in the future, sentiment research will undoubtedly play a significant role in ensuring excellent customer engagement and experience. The value of every new technology is determined not by the data acquired but by what is achieved with it. The promise of AI is not in eliminating the need to do so but in using tools to better understand the customers and then taking appropriate action depending on that understanding.

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References

1. Kang, M.Y.; Choi, Y.; Choi, J. The effect of celebrity endorsement on sustainable firm value: Evidence from the Korean telecommunications industry. *Int. J. Advert.* **2019**, *38*, 563–576. [CrossRef]
2. Chaki, S. *Enterprise Information Management in Practice*; Springer: Berlin/Heidelberg, Germany, 2015.
3. Kahaner, L. *Competitive Intelligence: How to Gather Analyze and Use Information to Move Your Business to the Top*; Simon and Schuster: New York, NY, USA, 1997.
4. Tuan, L.T. Organisational ambidexterity and supply chain agility: The mediating role of external knowledge sharing and moderating role of competitive intelligence. *Int. J. Logist. Res. Appl.* **2016**, *19*, 583–603. [CrossRef]
5. Tang, H.; Tan, S.; Cheng, X. A survey on sentiment detection of reviews. *Expert Syst. Appl.* **2009**, *36*, 10760–10773. [CrossRef]
6. Yiran, Y.; Srivastava, S. Aspect-based Sentiment Analysis on mobile phone reviews with LDA. In Proceedings of the 2019 4th International Conference on Machine Learning Technologies, Nanchang, China, 21–23 June 2019; pp. 101–105.

7. Anjaria, M.; Guddeti, R.M.R. A novel sentiment analysis of social networks using supervised learning. *Soc. Netw. Anal. Min.* **2014**, *4*, 181. [CrossRef]
8. Ramaswamy, S.; DeClerck, N. Customer perception analysis using deep learning and NLP. *Procedia Comput. Sci.* **2018**, *140*, 170–178. [CrossRef]
9. Ajmal, A.; Aldabbas, H.; Amin, R.; Ibrar, S.; Alouffi, B.; Gheisari, M. Stress-Relieving Video Game and Its Effects: A POMS Case Study. *Comput. Intell. Neurosci.* **2022**, *2022*, 4239536. [CrossRef]
10. Liu, L.; Dzyabura, D.; Mizik, N. Visual listening in: Extracting brand image portrayed on social media. *Mark. Sci.* **2020**, *39*, 669–686. [CrossRef]
11. He, W.; Zha, S.; Li, L. Social media competitive analysis and text mining: A case study in the pizza industry. *Int. J. Inf. Manag.* **2013**, *33*, 464–472. [CrossRef]
12. Dey, L.; Haque, S.M.; Khurdiya, A.; Shroff, G. Acquiring competitive intelligence from social media. In Proceedings of the 2011 Joint Workshop on Multilingual OCR and Analytics for Noisy Unstructured Text Data, Beijing, China, 17 September 2011; pp. 1–9.
13. He, W.; Yan, G. Mining blogs and forums to understand the use of social media in customer co-creation. *Comput. J.* **2015**, *58*, 1909–1920. [CrossRef]
14. He, W.; Tian, X.; Chen, Y.; Chong, D. Actionable social media competitive analytics for understanding customer experiences. *J. Comput. Inf. Syst.* **2016**, *56*, 145–155. [CrossRef]
15. Stieglitz, S.; Dang-Xuan, L. Emotions and information diffusion in social media—Sentiment of microblogs and sharing behavior. *J. Manag. Inf. Syst.* **2013**, *29*, 217–248. [CrossRef]
16. Yang, J.; Xiu, P.; Sun, L.; Ying, L.; Muthu, B. Social media data analytics for business decision making system to competitive analysis. *Inf. Process. Manag.* **2022**, *59*, 102751. [CrossRef]
17. Sotiriadou, P.; Brouwers, J.; Le, T.-A. Choosing a qualitative data analysis tool: A comparison of NVivo and Leximancer. *Ann. Leis. Res.* **2014**, *17*, 218–234. [CrossRef]
18. Singh, A.; Shukla, N.; Mishra, N. Social media data analytics to improve supply chain management in food industries. *Transp. Res. Part E Logist. Transp. Rev.* **2018**, *114*, 398–415. [CrossRef]
19. Ramanathan, U.; Subramanian, N.; Parrott, G. Role of social media in retail network operations and marketing to enhance customer satisfaction. *Int. J. Oper. Prod. Manag.* **2017**, *37*, 105–123. [CrossRef]
20. Ramasamy, L.K.; Kadry, S.; Nam, Y.; Meqdad, M.N. Performance analysis of sentiments in Twitter dataset using SVM models. *Int. J. Electr. Comput. Eng.* **2021**, *11*, 2275–2284. [CrossRef]
21. Burdisso, S.G.; Errecalde, M.; Montes-y-Gómez, M. A text classification framework for simple and effective early depression detection over social media streams. *Expert Syst. Appl.* **2019**, *133*, 182–197. [CrossRef]
22. Collobert, R.; Weston, J.; Bottou, L.; Karlen, M.; Kavukcuoglu, K.; Kuksa, P. Natural language processing (almost) from scratch. *J. Mach. Learn. Res.* **2011**, *12*, 2493–2537.
23. Palomino, M.A.; Aider, F. Evaluating the Effectiveness of Text Pre-Processing in Sentiment Analysis. *Appl. Sci.* **2022**, *12*, 8765. [CrossRef]
24. Haddi, E.; Liu, X.; Shi, Y. The role of text pre-processing in sentiment analysis. *Procedia Comput. Sci.* **2013**, *17*, 26–32. [CrossRef]
25. Nhlabano, V.; Lutu, P. Impact of text pre-processing on the performance of sentiment analysis models for social media data. In Proceedings of the 2018 International Conference on Advances in Big Data, Computing and Data Communication Systems (icABCD), Durban, South Africa, 6–7 August 2018; pp. 1–6.
26. Akhtar, M.J.; Ahmad, Z.; Amin, R.; Almotiri, S.H.; Al Ghamdi, M.A.; Aldabbas, H. An efficient mechanism for product data extraction from e-commerce websites. *Comput. Mater. Contin.* **2020**, *65*, 2639–2663.
27. Mangold, W.G.; Faulds, D.J. Social media: The new hybrid element of the promotion mix. *Bus. Horiz.* **2009**, *52*, 357–365. [CrossRef]
28. Kanakaraj, M.; Guddeti, R.M.R. NLP based sentiment analysis on Twitter data using ensemble classifiers. In Proceedings of the 2015 3Rd International Conference on Signal Processing, Communication and Networking (ICSCN), Chennai, India, 26–28 March 2015; pp. 1–5.
29. Castillo, M.J.; Taherdoost, H. The Impact of AI Technologies on E-Business. *Encyclopedia* **2023**, *3*, 107–121. [CrossRef]
30. O'Sullivan, S.; Nevejans, N.; Allen, C.; Blyth, A.; Leonard, S.; Pagallo, U.; Holzinger, K.; Holzinger, A.; Sajid, M.I.; Ashrafian, H. Legal, regulatory, and ethical frameworks for development of standards in artificial intelligence (AI) and autonomous robotic surgery. *Int. J. Med. Robot. Comput. Assist. Surg.* **2019**, *15*, e1968. [CrossRef]
31. Peng, G.C.; Alber, M.; Buganza Tepole, A.; Cannon, W.R.; De, S.; Dura-Bernal, S.; Garikipati, K.; Karniadakis, G.; Lytton, W.W.; Perdikaris, P. Multiscale modeling meets machine learning: What can we learn? *Arch. Comput. Methods Eng.* **2021**, *28*, 1017–1037. [CrossRef]
32. Taherdoost, H. Blockchain Technology and Artificial Intelligence Together: A Critical Review on Applications. *Appl. Sci.* **2022**, *12*, 12948. [CrossRef]
33. Yang, L.; Li, Y.; Wang, J.; Sherratt, R.S. Sentiment Analysis for E-Commerce Product Reviews in Chinese Based on Sentiment Lexicon and Deep Learning. *IEEE Access* **2020**, *8*, 23522–23530. [CrossRef]
34. Hung, M.; Lauren, E.; Hon, E.S.; Birmingham, W.C.; Xu, J.; Su, S.; Hon, S.D.; Park, J.; Dang, P.; Lipsky, M.S. Social network analysis of COVID-19 sentiments: Application of artificial intelligence. *J. Med. Internet Res.* **2020**, *22*, e22590. [CrossRef]
35. Yi, S.; Liu, X. Machine learning based customer sentiment analysis for recommending shoppers, shops based on customers' review. *Complex Intell. Syst.* **2020**, *6*, 621–634. [CrossRef]

36. Patel, K.; Mehta, D.; Mistry, C.; Gupta, R.; Tanwar, S.; Kumar, N.; Alazab, M. Facial Sentiment Analysis Using AI Techniques: State-of-the-Art, Taxonomies, and Challenges. *IEEE Access* **2020**, *8*, 90495–90519. [CrossRef]
37. Zhao, H.; Liu, Z.; Yao, X.; Yang, Q. A machine learning-based sentiment analysis of online product reviews with a novel term weighting and feature selection approach. *Inf. Process. Manag.* **2021**, *58*, 102656. [CrossRef]
38. Feizollah, A.; Ainin, S.; Anuar, N.B.; Abdullah, N.A.B.; Hazim, M. Halal Products on Twitter: Data Extraction and Sentiment Analysis Using Stack of Deep Learning Algorithms. *IEEE Access* **2019**, *7*, 83354–83362. [CrossRef]
39. Paredes-Valverde, M.A.; Colomo-Palacios, R.; Salas-Zárate, M.D.P.; Valencia-García, R. Sentiment Analysis in Spanish for Improvement of Products and Services: A Deep Learning Approach. *Sci. Program.* **2017**, *2017*, 1329281. [CrossRef]
40. Nandal, N.; Tanwar, R.; Pruthi, J. Machine learning based aspect level sentiment analysis for Amazon products. *Spat. Inf. Res.* **2020**, *28*, 601–607. [CrossRef]
41. Chakriswaran, P.; Vincent, D.R.; Srinivasan, K.; Sharma, V.; Chang, C.Y.; Reina, D.G. Emotion AI-driven sentiment analysis: A survey, future research directions, and open issues. *Appl. Sci.* **2019**, *9*, 5462. [CrossRef]
42. Mehta, P.; Pandya, S.; Kotecha, K. Harvesting social media sentiment analysis to enhance stock market prediction using deep learning. *PeerJ Comput. Sci.* **2021**, *7*, e476. [CrossRef]
43. Jourdan, Z.; Rainer, R.K.; Marshall, T.E. Business intelligence: An analysis of the literature. *Inf. Syst. Manag.* **2008**, *25*, 121–131. [CrossRef]
44. Taherdoost, H. Machine Learning Algorithms: Features and Applications. In *Encyclopedia of Data Science and Machine Learning*; IGI Global: Hershey, PA, USA, 2023; pp. 938–960.
45. Al Sonosy, O.; Rady, S.; Badr, N.L.; Hashem, M. A study of spatial machine learning for business behavior prediction in location based social networks. In Proceedings of the 2016 11th International Conference on Computer Engineering & Systems (ICCES), Cairo, Egypt, 20–21 December 2016; pp. 266–272.
46. Singh, B.; Kushwaha, N.; Vyas, O.P. An interpretation of sentiment analysis for enrichment of Business Intelligence. In Proceedings of the 2016 IEEE Region 10 Conference (TENCON), Singapore, 22–25 November 2016; pp. 18–23.
47. Chen, J.-H.; Huang, C.-W.; Cheng, C.-W. The monitoring system of Business support system with emergency prediction based on machine learning approach. In Proceedings of the 2016 18th Asia-Pacific Network Operations and Management Symposium (APNOMS), Kanazawa, Japan, 5–7 October 2016; pp. 1–4.
48. Ghiassi, M.; Zimbra, D.; Lee, S. Targeted twitter sentiment analysis for brands using supervised feature engineering and the dynamic architecture for artificial neural networks. *J. Manag. Inf. Syst.* **2016**, *33*, 1034–1058. [CrossRef]
49. Giatsoglou, M.; Vozalis, M.G.; Diamantaras, K.; Vakali, A.; Sarigiannidis, G.; Chatzisavvas, K.C. Sentiment analysis leveraging emotions and word embeddings. *Expert Syst. Appl.* **2017**, *69*, 214–224. [CrossRef]
50. Alantari, H.J.; Currim, I.S.; Deng, Y.; Singh, S. An empirical comparison of machine learning methods for text-based sentiment analysis of online consumer reviews. *Int. J. Res. Mark.* **2022**, *39*, 1–19. [CrossRef]
51. Yadav, V.; Verma, P.; Katiyar, V. E-commerce product reviews using aspect based Hindi sentiment analysis. In Proceedings of the 2021 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 27–29 January 2021; pp. 1–8.
52. Desai, Z.; Anklesaria, K.; Balasubramaniam, H. Business Intelligence Visualization Using Deep Learning Based Sentiment Analysis on Amazon Review Data. In Proceedings of the 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India, 6–8 July 2021; pp. 1–7.
53. Devika, M.; Sunitha, C.; Ganesh, A. Sentiment analysis: A comparative study on different approaches. *Procedia Comput. Sci.* **2016**, *87*, 44–49. [CrossRef]
54. Cambria, E.; Das, D.; Bandyopadhyay, S.; Feraco, A. Affective computing and sentiment analysis. In *A Practical Guide to Sentiment Analysis*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 1–10.
55. Tripathy, A.; Agrawal, A.; Rath, S.K. Classification of sentiment reviews using n-gram machine learning approach. *Expert Syst. Appl.* **2016**, *57*, 117–126. [CrossRef]
56. Zhang, H.; Cao, X.; Ho, J.K.; Chow, T.W. Object-level video advertising: An optimization framework. *IEEE Trans. Ind. Inform.* **2016**, *13*, 520–531. [CrossRef]
57. Poria, S.; Cambria, E.; Gelbukh, A.; Bisio, F.; Hussain, A. Sentiment data flow analysis by means of dynamic linguistic patterns. *IEEE Comput. Intell. Mag.* **2015**, *10*, 26–36. [CrossRef]
58. Wünderlich, N.V.; Heinonen, K.; Ostrom, A.L.; Patricio, L.; Sousa, R.; Voss, C.; Lemmink, J.G. "Futurizing" smart service: Implications for service researchers and managers. *J. Serv. Mark.* **2015**, *29*, 442–447. [CrossRef]