An Investigation of the Effectiveness of Sentiment Analysis in Understanding Consumer Brand Acceptance and Loyalty: A Scoping Review

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Abstract

With the rapid advancement of product offerings in the global market, many brands recognise the importance of online brand communities in shaping customers' purchasing behaviours. As consumers readily express their thoughts on companies, products, and services to fellow Internet users, prospective customers easily access these real-time online reviews. While it may be challenging to quantify brand acceptance levels precisely, evaluating the ratio of positive to negative comments about a brand could provide valuable insights into consumer perceptions of its products, services, and overall identity. Therefore, this study aims to explore the significance of sentiment analysis as a valuable marketing tool for brands in assessing consumer acceptance of their brand. Following a review of relevant literature, findings underscore the critical relevance of understanding consumers' views toward a brand as a critical business concept, emphasising the need to study people's opinions, attitudes, assessments, and emotions represented in written texts to extract new ideas. In the light of this, it is recommended that brands build a team of skilled and technologically adept professionals capable of efficiently analysing and reporting brands' acceptance levels across all social media platforms.

Keywords: Online brand communities, Consumer perceptions, Sentiment analysis, Personalised marketing strategies.

Introduction

In this modern age where rapid global market development is the new order, fierce competition has influenced many organisations to reconsider brand perception. Thus, for a firm to have a superior brand perception, it must have a clear and superior brand image (Sutaguna, Fardiansyah, Hendrayani, & Yusuf, 2023). According to Ebrahim (2020), brands take advantage of the internet through social media platforms to achieve their market acceptance strategy. The advent of the Internet has brought about a paradigm shift in information sharing and disrupted conventional modes of information dissemination (Li & Zhang, 2021).

The widespread availability of the internet has resulted in a massive influx of data, presenting a valuable opportunity to uncover consumer sentiments regarding purchased and experienced products. Consequently, organisations are keen on harnessing these data to extract meaningful insights that facilitate informed decision-making (He, Wang, & Akula, 2017). This is achieved through the process of analysing the diverse and abundant dataset, which is mostly referred to as "big data" (Yuzhong, 2021).

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The exploration of consumer comments in social media and other online forums has emerged as a powerful resource for identifying valuable consumer insights (Vriens, Chen, & Vidden, 2019). User-generated content (UGC) in the form of these comments offers a viable route for discovering customer demands while also providing an alternative source of information (Uzunkaya, 2020). As a result, mining and analysing UGC, particularly the opinions and sentiments expressed by consumers, are undoubtedly valuable for businesses seeking a better knowledge of their customers.

UGC has gained widespread acceptance among researchers as a beneficial resource for making informed marketing decisions. Brand acceptability is one area of particular interest, as online reviews have the potential to influence brand image, brand positioning, and even design decisions (Guo, Bai, Yu, Zhao, & Wan, 2021). Researchers frequently use sentiment analysis to extract insights from UGC, a technique that involves processing natural language to analyse and grasp human emotions (Kang, Cai, Tan, Huang, & Liu, 2020). Researchers can delve into the sentiments expressed in online reviews using sentiment analysis in order to acquire a better grasp of consumer opinions and emotions toward brands.

One application of sentiment analysis is in analysing textual data from Twitter, which provides important insights into two crucial metrics: polarity and subjectivity (Srivastava, Singh, & Drall, 2019). Subjectivity relates to the degree of personal opinion expressed in the text, whereas polarity refers to whether the sentiment is good, negative, or neutral (Yadollahi, Shahraki, & Zaiane, 2017). Organisations can get information about their brand awareness levels by using sentiment analysis on Twitter data. This enables them to understand the overall sentiment and subjective opinions expressed by Twitter users towards their brand and helps organisations assess their brand perception in the online sphere.

From a psychological standpoint, brand awareness encompasses consumers' collective psychological perceptions regarding a brand's products and services. Brand image, on the other hand, is divided into two primary dimensions: functional attributes and emotional value (Feng, Yu, Yang, & Yi, 2021). The functional attribute dimension represents users' perceptions of the brand's practical features, while the emotional dimension reflects the brand's subjective value and the emotions it evokes in consumers. Consumer perception of a brand, therefore, encompasses the overall impression and evaluation that a consumer forms regarding the brand (Guo, Bai, Yu, Zhao, & Wan, 2021).

Evaluating brand image is a critical aspect of comprehending brand awareness and serves as the initial stage in enhancing brand quality and formulating effective brand communication strategies. Enterprises have a means of objectively assessing their brand image (Ferreiro-Rosende, Fuentes-Moraleda, & Ferreiro-Rosende, 2021). This enables companies to gain a deeper understanding of consumers' psychological perceptions, allowing for the development of precise marketing strategies that cater to individual preferences.

Sentiment analysis has been adopted in various fields of endeavours. For example, in healthcare, sentiment analysis provides a view into patients' healthcare issues, which helps decision-makers make plans and changes to solve these problems on time (Abualigah, Alfar, Shehab, & Hussein, 2020). In finance, investors have found sentiment analysis a useful tool because of the influences it has on brand reputation and the prices of stocks. Studies have shown that sentiment analysis focused on stock price forecast and financial news, trends in the international financial market, and foreign exchange have been utilised to forecast corporate earnings (Curme, Stanley, & Vodenska, 2015; Day & Lee, 2016; Souma, Vodenska, & Aoyama, 2019; Mishev et al., 2019). In tourism, sentiment analysis serves as a useful tool in determining the attitude of visitors towards visited locations and services (Hasyim, Omar, Ba-Anqud, & Al-Samarraie, 2020).

Gräbner, Zanker, Fliedl, and Fuchs (2012) suggest that social media, websites, and travel blogs have served as major sources of data for extracting the opinions of tourists about places visited. According to Fan, Xi, and Li (2018), sentimental analysis assists manufacturers in uncovering consumer demands and requirements, providing valuable insights into the needs of the target market. Also, it facilitates the design of new products by offering guidance and inspiration for innovative ideas. This study takes a conceptual review of sentiment analysis as an effective tool for firms to analyse customers' opinions about their brands, which can provide opportunities for competition.

For structure, the paper is divided into seven major sections. Section 1 examines the purpose and objective of the study as well as its research questions. Section 2 discusses the literature on sentiment analysis, the implication of sentiment analysis, features and indicators as well as challenges in drawing insights from sentiment analysis, and brand awareness and acceptance; section 3 presents the paper's methodology, discussing in detail the procedures carried out in the analysis of the topic under review. Section 4 presents the discussion of findings from the review of current literature. In section 5, the authors conclude from the literature analysis carried out. Section 6 focuses on the contribution of the authors of this paper. Section 7 highlights the limitations and future research.

Research purpose and rationale

In the evolving information communication landscape, the proliferation of user-generated content presents both remarkable opportunities and challenges for mining brand image (Ferreiro-Rosende et al., 2021). Leveraging user-generated data, social networks offer enhanced operability, flexibility and feasibility in the assessment of brand image. The application of natural language processing techniques to analyse the sentiment tendencies of user-generated texts about specific topics represents a recent trend in brand image assessment and holds significant practical value (Feng, Yu, Yang, & Yi, 2021).

In today's fast-paced digital world, a vast number of reviews are generated daily, posing a challenge for consumers in making informed purchase decisions. The digital landscape facilitates the rapid dissemination of information among users, influencing the sentiments and perceptions of others towards a particular event or product. Consequently, comprehending the collective sentiment of the masses becomes crucial (Srivastava, Singh, & Drall, 2019).

Brand perception serves as a fundamental component in assessing brand image. With the exponential growth of topic-specific texts, a vast pool of data is available for conducting brand perception analysis. Traditional brand evaluation methods relying on questionnaire surveys are no longer adequate to meet the current requirements for brand image evaluation (Singh, Bajpai, & Kulshreshtha, 2021). As a result, this study concentrates on brand research utilising sentiment analysis techniques applied to topic-specific texts.

Sentiment Analysis

Sentiment refers to an individual's emotional state, perception, or opinion towards something. Sentiment analysis is a methodological process that aims to ascertain the polarity of sentiment expressed in a text, which can be categorised as positive, neutral, or negative (Deho, Agangiba, Aryeh, & Ansah, 2018).

Sentiment analysis leads to the identification of arguments and opinions in a text, which forms an aspect of opinion mining. It pinpoints statements that agree or disagree, stating the feeling or thought of negativity, positivity, or neutrality in reviews or comments (Li, Chen, Zhong, Gong, & Han, 2022). Researchers are investigating consumer responses to products and services by examining online reviews, feedback, and blogging platforms (Lin et al., 2017). To explore online consumer reviews, researchers utilise various text analytical tools such as word clouds (Miley & Read, 2011), word extraction algorithms (Barth, Kobourov, & Pupyrev, 2014), word storms (Castellà & Sutton, 2014), sentiment score analysis methodologies (Lakshmi, Harika, Bavishya, & Harsha, 2017), and frameworks for analysing emojis (Li, Ch’ng, Chong, & See 2018). These tools allow researchers to explore the substance of online consumer reviews and gain significant insights.

According to Pak and Paroubek (2016), as online markets, merchants and online retailers continue to grow in popularity, there is an increasing need for feedback from buyers about purchased products. Thus, sentiment analysis techniques are instrumental in analysing opinionated text that encompasses consumer sentiments towards companies, events, brands, or products. Sentiment analysis entails automatically classifying text based on its valence (Vriens, Chen, & Vidden, 2019). Joshi, Prajapati, Shaikh, and Vala (2017) added that by utilising sentiment analysis techniques, valuable information can be drawn from the opinions of users. Fan et al. (2018) observed that certain techniques categorise comments into two classes, namely negative or positive, while others adopt a more nuanced approach that encompasses multiple sentiment classes.

Furthermore, sentiment analysis quantifies consumers' attitudes towards brands by assigning brand scores. This enables companies to gain a more intuitive and objective understanding of consumers' perspectives, identify the strengths and weaknesses of brand images, and receive decision support for resource allocation and adjustments to product strategies (Uzunkaya, 2020).

In the present era of information technology, online purchasing has become effortless for consumers, who can readily share their experiences and opinions through social media platforms. This user-generated content holds significant influence over potential customers and can greatly impact their purchasing decisions in the future (Yuzhong, 2021). The ease with which individuals can share their thoughts on companies, products, and services with other internet users is coupled with the seamless accessibility of online reviews in real time for potential customers. Despite the abundance of social reviews, organisations have yet to fully capitalise on them for product improvement and measuring brand acceptance. While there is no definitive method to measure brand acceptance levels, analysing the ratio of positive to negative comments about a brand can provide valuable insights into how consumers perceive its products, services, and overall brand persona.

Brand Acceptance and Awareness

Brand awareness is defined by Keller and Brexendorf (2019) as the degree to which customers can recognise or recall a brand name through its logo and other diverse circumstances. Similarly, Foroudi, Jin, Gupta, Foroudi, and Kitchen (2018) emphasised the importance of brand awareness, stating that it occurs when customers are aware of a brand and are more likely to choose it.

Keller and Brexendorf (2019) identified two phases of brand awareness. These are depth and breadth. These characteristics are critical in influencing customer behaviour. Depth refers to the ability of consumers to recall specific products associated with a brand when prompted with the brand name. On the other hand, width refers to the ease with which consumers can recognise a brand when searching for a product, enabling them to make informed decisions regarding whether to purchase or skip the brand.

Shabbir, Khan, and Khan (2017) emphasise that a brand name serves as a fundamental component of the brand awareness construct. Chakraborty (2019) added that brand awareness plays a critical role in driving market performance through market performance. Their research indicated that the impact of brand awareness on market performance was particularly pronounced in homogenous market segments. Similarly, Wei (2022) highlighted that establishing brand awareness was essential for cultivating competitiveness in dynamic markets. Thus, Pina and Dias (2021) concluded that the presence of brand awareness could elicit varied responses in how consumers process information. These citations are too old to be relevant in today's scholarship.

Findings from the research conducted by Oh (2016) revealed a positive correlation between brand awareness and consumers' perception of price fairness. Considering that consumers significantly influence the market and the intricate relationship between markets subsequently impacts the economy, it can be suggested that brand awareness, as a marketing and market factor, plays a vital role not only for companies but also in fostering and sustaining economic prosperity. Undoubtedly, branding adds value to products and services, thereby enhancing the value for manufacturers, consumers, and the overall market. Moreover, to comprehensively assess the impact of brand awareness on consumer behaviour, it is essential to measure brand credibility, brand reliability, and brand loyalty as well. Collectively, these factors contribute to a deeper understanding of the influence and significance of brand awareness in shaping consumer preferences and actions.

The analysis of collected data empowers businesses to enhance awareness regarding their brands, products, services, events, marketing campaigns, and overall market trends (Bekmamedova & Shanks, 2014; Ruhi, 2014; Kleindienst, Pfleger, & Schoch, 2015; Oh, Sasser, & Almahmoud, 2015). Within this context, three key goals related to awareness emerge: gaining insights into customer values and behaviours, understanding the impact and effectiveness of online marketing campaigns, and uncovering new ideas to bolster brand reputation and engagement (Bekmamedova & Shanks, 2014). Businesses are motivated by awareness to enhance and update their resources continuously, including sentiment analysis assets, to gain a deeper understanding of the content, context, and business implications of customer conversations (Bekmamedova & Shanks, 2014).

Understanding consumer sentiments about brands

According to Li, Chen, Zhong, Gong, and Han (2022), the widespread utilisation of micro-blog sites, product review platforms, and social media channels provides consumers with ample opportunities to share their views, feedback, and comments about products. Arbelles, Berry, and Theyyil (2020) argue that effectively managing this electronic word-of-mouth (eWOM) communication has emerged as a crucial strategy for marketers. For firms, sales value serves as a primary motivation to monitor eWOM activities.

To maintain brand trust, Bhandari and Rodgers (2018) conclude that it is essential for companies to respond and provide feedback on online platforms promptly. Social media sites, despite their popularity, can face challenges related to source credibility and content quality. However, blogs have the potential to counterbalance these issues by presenting alternative viewpoints and arguments against certain products (Pant, Hsieh, Lee, & Shen, 2014). Among the various social media platforms, Twitter stands out as a widely used microblogging site. Extracting user opinions from social media data is a complex task that can be approached in different ways. Also, Younis (2015) proposed an open-source methodology that involved collecting, pre-processing, analysing, and visualising Twitter microblog data using open-source tools. This approach was employed to conduct text mining and sentiment analysis on user-generated online reviews of two prominent retail stores in the UK, Tesco and Asda, during the Christmas period of 2014.

In the research by Gülcan and Bayram (2021), which examined content analysis in political participation during COVID-19, it was pointed out that billions of people engage in tweeting, sharing, posting, and discussing on various social media platforms every day. Thus, this surge in activity has led to the opening up of novel avenues for research into human behaviour, information diffusion, and the propagation of influence. The authors add that social media platforms present researchers with unparalleled opportunities to study these phenomena at an unprecedented scale. Similarly, Chaudhri, Saranya, and Dubey (2021) believe that the vast amount of data generated on social media has become a valuable resource for data mining and predictive analytics.

In comparing social media platforms with shopping sites, research by Erkan and Evans (2018) indicates that electronic word-of-mouth (eWOM) information found on shopping sites is perceived as more trustworthy compared to social media information. This is because shopping sites are generally regarded as having higher ratings in terms of content quality and source credibility. These outcomes align with Sharma, Morales-Arroyo, and Pandey (2011), who noted that the availability of online reviews and detailed product information on shopping sites proves to be beneficial in reducing consumer uncertainty during the purchase process. Additionally, Chatterjee (2001) affirms that these reviews have the potential to influence consumer behaviour by creating a patronising effect on retailers and counteracting negative information about them.

According to Hendrawan, Suryani, and Oktavia (2017), it is common for customers to read a minimum of ten product reviews before making a purchase decision. Sentiment scores derived from customer reviews play a crucial role in various applications. These scores are generated at the document level to assess the authors' overall tone or sentiment (Feldman, 2013). Consumer reviews and the opinions conveyed in them have a considerable impact on the purchasing decisions of consumers. Furthermore, Kau et al. (2019) highlighted that sentiment scores are useful for determining positive and negative aspects linked with products. As a result, sentiment scores connected with reviews can be used to analyse product performance or gauge consumer satisfaction with the product. They provide significant insights for businesses to understand customer perception better and make informed product decisions.

The Implication of Sentiment Analysis on Brand Acceptance

Research by Abu Bakar, Ahmad, and Ahmad (2019) noted that many organisations have included social media platforms in their marketing strategy. Simply put, companies are using platforms like Facebook and Twitter to provide a variety of services and communicate with their customers. Consequently, user-generated content is numerous and readily available on various social media platforms. This user-generated content is a significant resource for organisations to acquire insights, monitor customer sentiments, and communicate more directly and instantly with their target audience. Moreso, Sarin, Kar, and Ilavarasan (2021) highlighted that the widespread adoption of social media has opened up new avenues for businesses to connect with customers and leverage the power of user-generated content for various purposes, including brand promotion, customer support, and market research.

To enhance their competitive advantage and gain a comprehensive understanding of the business landscape, Dubey (2020) stated that companies must go beyond monitoring and analysing customer-generated content solely on their social media platforms. It is equally important for them to monitor and analyse textual information present on their competitors' social media sites. Analysing customer opinions through sentiment analysis offers businesses a valuable tool for comprehending their competitive value in a dynamic market and gaining insights into customer perceptions of their products and services. Through the analysis of consumer sentiments, Tiruwa, Yadav, and Suri (2016) opined that businesses can acquire a better knowledge of how their offerings are widely viewed and find opportunities for improvement. This information is crucial for shaping future marketing strategies and making informed decisions regarding product development, customer engagement, and overall business operations.

Results obtained from the research carried out by Markovic, Iglesias, Singh, and Sierra (2018) highlight that the value attached to a brand is important for that brand as it performs a crucial role in ensuring better customer relationships. This is an indication that brand management has become integral to a firm’s operation and, therefore, requires the firm to make conscious efforts to improve brand awareness, reputation, and customer loyalty. Analysing tweets relating to COVID-19 by Dep Learning Classifiers, Chakraborty et al. (2020) submit that the introduction and extensive use of social media has given customers the platform to engage, communicate, and share useful information with other users, which creates opportunities and challenges for businesses. Therefore, the digital world provides businesses with a great tool to interact with both current and prospective customers, enabling them to pass along their product and brand information (Kumar, Choi, & Greene, 2017).

However, Isah, Trundle, and Neagu (2014) noted that customer feedback is extremely important in the use of sentiment analysis as it assists organisations in taking appropriate measures for improving their products, services, and overall company strategy. This is highlighted in a study on the opinions and experiences of social media users with cosmetics and drug products. Consumer feedback is critical because it assists firms in identifying their strengths and areas for improvement. A study conducted by Ikoro, Sharmina, Malik, and Batista-Navarro (2018) shows this by comparing sentiment data from tweets made by consumers regarding the Big Six, the oldest and largest electric and gas supplier in the United Kingdom, and a new entrant energy consumer. According to the study's findings, attitudes toward the Big Six are largely unfavourable, whereas sentiment among new entrant energy consumers is more positive.

According to El Rahman, AlOtaibi, and AlShehri (2019), sentiment analysis provides business owners with various advantages, including the capacity to evaluate their popularity among customers and obtain insights into customer impressions of their products or services. It also enables companies to evaluate the efficacy of their brand communication and social media strategy (Poecze, Ebster, & Strauss, 2018). Furthermore, sentiment analysis, according to Suman, Gupta, and Sharma (2017), allows companies to assess the impact of social media on their stock price and overall business performance.

Additionally, the study by Yuliyanti, Djatna, and Sukoco (2017) shows that sentiment analysis on social media platforms can be used to check the effective nature of a programme. For example, the article analysed a tweet that was related to a community development project, and it was found that the comments were significantly positive. The implication here is that the information can be used as a mechanism to enhance the overall living standards of the community.

Key indicators of brand acceptance in sentiment analysis

Papachristopoulos and Tsakonas (2020) stated that the measurement of opinions and emotions can be challenging and complex. Opinions are inherently subjective and can differ among individuals and across different topics. For instance, discussing politics may carry significant importance, while choosing a restaurant may not hold the same level of significance. Moreover, the political views of an expert are typically considered more valuable compared to those of a student who may not have access to all the relevant information.

Gülcan and Bayram (2021) highlight three ways opinions can be grouped. They are direct, implicit and comparison opinions. Direct opinion, as implied, is stated directly. The comparison opinion refers to the direct comparison of two objects, products, or services based on specific parameters. Lastly, the implicit opinion category can be ambiguous and require careful interpretation. They may include elements such as sarcasm, phrases, and idioms that need to be correctly understood. For instance, in the statement, "The machine began to throttle just after three days," the presence of a problem with the engine is not explicitly mentioned, and thus, it needs to be accurately analysed in context.

Challenges associated with the application of Sentiment Analysis

According to Hajiali and Dubey (2020), machine analysis of the text can have difficulties in accurately interpreting the contextual usage of particular words or adjectives inside a phrase, resulting in less precise conclusions. To acquire a more refined and correct result, it is necessary to identify the tone and degree of tone expressed in the text, which may be accomplished by analysing various phrases and terms. However, the challenge here is determining whether the message being delivered is objective or subjective.

Ayan (2016) highlighted that one of the most challenging aspects of sentiment analysis is handling sarcasm and irony. The author emphasised that the expression of opinions by humans often involves implicit forms and diverse ways of formulating messages, presenting a significant challenge in sentiment analysis. Thus, such sentences can be misleading, as they may convey a negative sentiment while intending an overwhelmingly positive message, or vice versa.

Furthermore, some researchers, such as Jaganadh (2012), Li, Bruce, and Gao (2023), and Yazdinejad et al. (2022), believe that there exists a challenge in capturing the emotional source behind specific words when expressing feelings. While identifying the overall feeling of a line may be simple, recognising the exact emotional source might be tricky. Yazdinejad et al. (2022) sites and examples that consider the sentence: "I was looking forward to seeing them." This sentence conveys a positive feeling, but the exact source of that happiness, represented by "them," is not specified.

In examining the lexis of an enhanced collaborative network that targeted financial sentiment analysis, Shang, Xi, Hua, Tang, and Zhou (2023) observed that the challenge of indirectly extracting negative emotions arises when certain words or phrases, such as "no" or "refrain" are present in the text. Thus, these words can create a misleading and indirect sentiment, making it difficult to identify the intended negative emotion accurately. Also, sentiment analysis systems face challenges when it comes to identifying the source and author of a quoted sentence within a document. The text may not always be a direct quote from the document's author but rather a quote from another person not referenced by the author. Yazdinejad et al.2020, whose conclusion also supports this assertion, add that it becomes difficult for sentiment analysis systems to attribute the sentiment accurately to the appropriate source and author.

Approaching it from an IT angle, Van Dinh, Luu, and Nguyen (2022) argue that distinguishing between genuine customer opinions and spam texts intended to harm a company's reputation presents another challenge. To further corroborate this point, Yazdinejad et al. (2019) explain that the system may mistakenly classify negative comments as genuine, leading to inaccurate results.

Methodology

The paper employs a scoping review methodology as a key approach to conducting the literature review. The decision to employ a scoping review for this study is supported by the rationale put forth by Arksey and O'Malley (2005) and Higgins and Green (2011). They argue that a scoping review is valuable for providing a comprehensive overview of a wide range of literature sources, including both peer-reviewed publications and grey literature, on a broad topic. Scoping reviews are particularly advantageous when the literature is diverse and complex. By conducting a scoping review, decision-makers can gain valuable insights into the nature of a specific concept and how it has been studied and examined in the literature over time (Peters et al., 2020).

This paper follows the five-stage structure by Arksey and O'Malley (2005), which is to establish the research questions, determine relevant studies, select appropriate studies, chart relevant data, and collate and summarise the data.

Establishing the Research Questions

Research Questions

The paper aims to address the following questions.

1. What are the ways sentiment analysis has been used to detect shifts or changes in consumer sentiment towards brands over time?
2. What are the identified potential implications for applying sentiment analysis in enhancing brand acceptance by brand managers and marketers?
3. What are the common challenges that organisations face while drawing insights from customer sentiments?
4. What recommendations have been provided for organisations regarding the use of sentimental analysis in predicting their brand acceptance?

Determine relevant studies

The authors conducted a comprehensive search of literature through the adoption of the PRISMA framework, consisting of the identification, screening, and inclusion phases (Gopi, Jyothi, Narayana, & Sandeep, 2023). The authors searched five credible and reputable online databases for relevant papers. These databases are Science Direct, Emerald Insight, Scopus, IEEE, and the Association of Computing Machinery (ACM).

Strings of keywords such as sentiment analysis, consumer loyalty, brand acceptance, opinion mining, and social media were searched on all identified databases. Emphasis was on literature published in English between 2018 and 2023.

Selecting Articles

Following the scoping review protocol as outlined by Levac, Colquhoun, and O'Brien (2010), two reviewers independently assessed titles and abstracts for all citations obtained through the literature search based on the selection criteria. Full texts of citations identified as potentially eligible by either reviewer were then retrieved. A total of 1356 articles were found on these databases, out of which 56 articles emerged from the screening conducted based on inclusion and exclusion measures. Subsequently, after reading and analysing the full texts, 22 articles were obtained for final use. In arriving at this figure, the reviewers individually examined the full texts, applying the same selection criteria, and compared their lists of included and excluded studies as earlier described. Through the participation of a third reviewer, discussions were held to resolve disagreements and reach an agreement. Documents agreed by both reviewers to be eligible were included. Microsoft Excel was then utilised to facilitate the screening of titles and abstracts and the selection of full-text studies. This process of selection is visually represented in a flow chart following the PRISMA extension for scoping reviews.

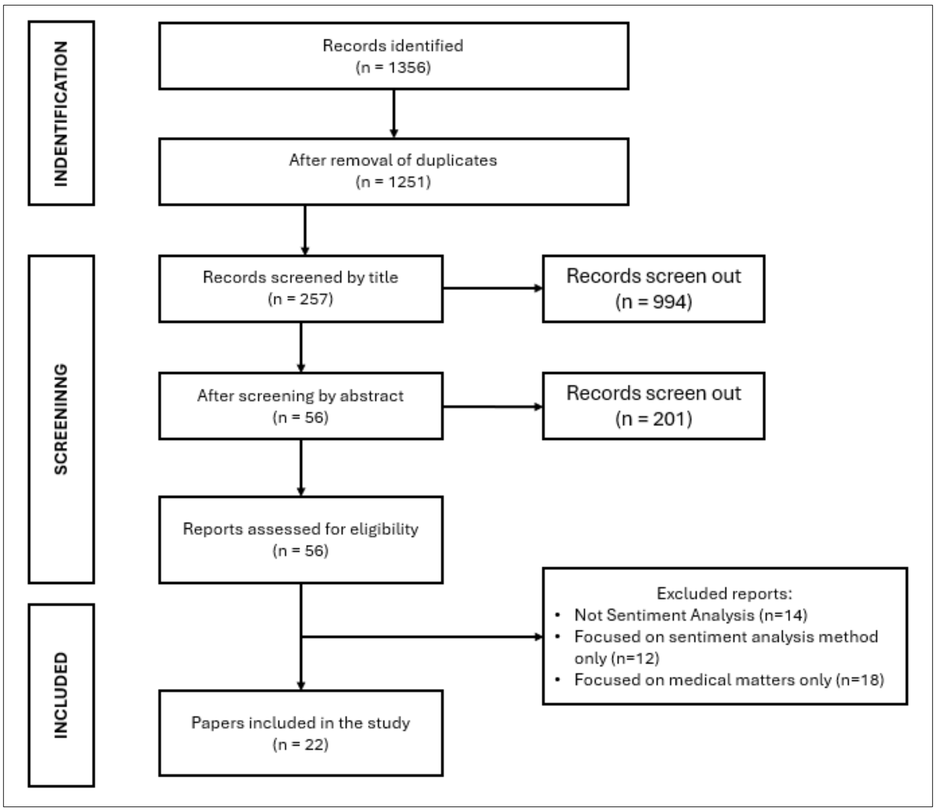

Figure 1: The systematic literature review process

Charting the data

The fourth step in the review process entails a thorough examination of the text, involving multiple readings to pinpoint and systematically organise key emerging themes that either support or contradict the evolving ideas found in all the papers incorporated in the review (Ritchie & Spencer, 1994). To streamline this process, a standardised data extraction sheet was prepared and continuously refined as the included papers became more familiar. This sheet was designed to encompass all pertinent aspects aligned with the research objective and questions. Descriptive

characteristics, such as author(s), setting, country, and the study design, along with detailed descriptions of each paper's study aims, methodology, and results were included. Data were then extracted based on this framework.

Findings and Discussion

Research question one: What are the ways sentiment analysis can detect shifts or changes in consumer sentiment towards brands over time?

In their work, Benamara, Chardon, Mathieu, and Popescu (2011) utilised a subjectivity classification method at the segment level, which is particularly suitable for discourse-based sentiment analysis. This approach incorporates both local and international context characteristics to automatically differentiate between implicit and explicit opinions, as well as between subjective non-evaluative segments and objective ones. Younis (2015) presented a methodology based on open-source tools for collecting, pre-processing, analysing, and visualising Twitter microblog data. This approach was utilised to perform text mining and sentiment analysis on user-generated online reviews of Tesco and Asda, two prominent retail stores in the UK, specifically focusing on the Christmas period in 2014. Karimi and Shakery (2017) proposed a language model-based framework that aids in subjectivity detection. They introduced a scoring formula based on differences, which helps minimise the impact of commonly occurring topic-relevant words during the process of distinguishing between subjective and objective documents. Yue, Chen, Li, Zuo, and Yin (2019) presented a rule-based classifier that categorises sentences with strong subjective clues into the subjective category. This system leverages the AutoSlog-TS information extraction system to learn new patterns for objective sentences by identifying syntactic templates.

Also, Liu (2012), Sun, Luo, and Chen (2017), Yue, Chen, Li, Zuo, and Yin (2019), Zucco, Calabrese, Agapito, Guzzi, and Cannataro (2020) present a comprehensive overview of different types of opinions in opinion mining, highlighting their characteristics and comparisons. The discussed types include regular and comparative opinions, explicit and implicit opinions, subjectivity, and emotion. Within regular sentiment, two main sub-types are identified: direct sentiment and indirect sentiment. Direct sentiment refers to opinions that express judgments directly about an object or a specific aspect of the object. On the other hand, indirect sentiment involves expressing opinions on an object or its aspects indirectly. Explicit and implicit opinions are categorised based on the presence of subjectivity in the statement. An explicit opinion is a subjective statement that explicitly expresses a comparative or regular opinion. On the other hand, an implicit opinion is an objective statement that implicitly conveys a comparative or regular opinion. Subjectivity and emotion are interconnected concepts in opinion mining. Subjectivity refers to the expression of personal feelings, views, or beliefs in a sentence. Emotions, on the other hand, are subjective experiences and thoughts that are closely associated with sentiments. The intensity of certain emotions, such as joy and anger, often correlates with the strength of a sentiment or an opinion.

Research question two: What are the potential implications for applying sentiment analysis in enhancing brand acceptance by brand managers and marketers?

It was observed in the study carried out by Fan and Gordon (2014) and Kleindienst et al. (2015) that sentiment analysis can assist marketing managers in customer segmentation, enabling them to customise marketing materials with greater precision. This finding was also supported in the study by Ansari, Almunawar, Lim, and Al-Mudimigh (2019), as well as

(Ibrahim & Wang, 2019). In another study by Tiruwa, Yadav, and Suri (2016), examining the sentiments expressed by customers allows businesses to gain a deeper understanding of how their offerings are perceived and identify areas for improvement. This information is crucial for shaping future marketing strategies and making informed decisions regarding product development, customer engagement, and overall business operations. Suman, Gupta, and Sharma (2017) highlight that sentiment analysis enables businesses to evaluate the impact of social media on their stock price and overall business performance. Similarly, in El Rahman, AlOtaibi, and AlShehri (2019), sentiment analysis is argued to offer business owners several benefits, including the ability to gauge their popularity among customers and gain insights into customer perceptions of their products or services.

Furthermore, studies by Feldman (2013), Bekmamedova and Shanks (2014), Fan and Gordon (2014), Ruhi (2014), Kleindienst et al. (2015), and Oh et al. (2015) highlighted that sentiment analysis enables businesses to track and monitor customers' comments, opinions and reviews about their brands and products. This capability helps businesses create and evaluate marketing strategies and understand the impact and effectiveness of marketing campaigns and messages. Poecze, Ebster, and Strauss (2018) added that it allows businesses to assess the effectiveness of their brand communication and social media strategies. Through the utilisation of sentiment analysis, a business can effectively analyse a competitor's strategy by monitoring and tracking their products, brand, and services (Kurniawati, Shanks, & Bekmamedova, 2013; Kleindienst et al., 2015; Montoyo, Martínez-Barco, & Balahur, 2012; Ribarsky, Wang, & Dou, 2014). Extracting actionable insights from the available data through sentiment analysis provides valuable competitive intelligence, enabling a better understanding of the business environment and competitors (Fan & Gordon, 2014; Jayasanka et al., 2014; Ribarsky et al., 2014).

Research question three: What are the challenges that organisations are likely to face while drawing insights from customer sentiments?

The nature of collected data, particularly from social media, often presents challenges due to its contextual sensitivity, informality, and conciseness, making it difficult to establish meaningful connections and understand the broader context (Best, Bruce, Dowson, Love, & McGrath, 2012; Mosley Jr, 2012). The distributed nature and the lack of structure of large volumes of data further complicate the extraction of useful and practical information (Mayeh, Scheepers, & Valos, 2012; Ribarsky et al., 2014). In Yazdinejad et al. (2022) and Li, Bruce, and Gao (2023), it was pointed out that there exists a challenge in capturing the emotional source behind specific words when expressing feelings. While it may be straightforward to identify the overall sentiment of a sentence, determining the exact emotional source can be difficult.

Another challenge encountered is distinguishing between genuine customer opinions and spam texts intended to harm a company's reputation (Van Dinh, Luu, & Nguyen, 2022). The system may mistakenly classify negative comments as genuine, leading to inaccurate results (Yazdinejad et al., 2019). The language employed in the collected data often incorporates special symbols, slang, and occasionally pictorial representations with inherent meanings. Effectively understanding and capturing sentiment within these symbols and slang in a structured manner poses a challenge (Nazir, Rao, Wu, & Sun, 2020)). Additionally, language-related complexities arise when businesses aim to monitor and analyse consumer comments and reviews in multiple languages, further complicating the sentiment analysis (Li, Chen, Zhong, Gong, & Han, 2022).

Research question four: What recommendations can be provided for organisations regarding the use of sentimental analysis in predicting their brand acceptance?

Business managers should invest in advanced sentiment analysis tools that leverage machine learning algorithms, natural language processing, and semantic analysis. These tools can help in analysing customer feedback, comments, and reviews more accurately and efficiently, enabling you to make data-driven decisions. Business organisations can utilise sentiment analysis to segment customers based on their sentiments and preferences. Furthermore, they can tailor their marketing materials and campaigns to resonate with specific customer segments, enhancing customer engagement and satisfaction. Using sentiment analysis, managers can track and analyse their competitors' brand perceptions, product offerings, and marketing strategies. This can be done by identifying areas of opportunity and potential threats, allowing for adjustments in strategies and staying ahead of the competition.

It is important to acknowledge the language-related challenges in sentiment analysis, such as slang, special symbols, and multilingual comments. A way to do this is through employing language models and sentiment analysis tools that are capable of understanding diverse languages and capturing sentiment nuances accurately. Explore advanced analytics techniques, such as social network analysis and text mining, to gain deeper insights from sentiment analysis. Uncover patterns, trends, and correlations in customer sentiments, enabling you to make more informed decisions and identify emerging market trends. Additionally, it is important to keep up with the evolving sentiment analysis techniques and technologies. Stay updated with the latest research and advancements in the field to ensure that the sentiment analysis efforts remain effective and aligned with industry best practices.

Conclusion

This paper has focused on shedding light on the challenges and opportunities associated with sentiment analysis. From understanding the different types of opinions, such as explicit and implicit opinions, to considering the complexities of language and context, businesses need to adopt robust sentiment analysis methodologies and tools to extract meaningful insights from the vast amounts of unstructured data available effectively. Sentiment analysis has emerged as a valuable tool for businesses to gain insights into customer opinions, sentiments, and preferences. Through the analysis of customer feedback, comments, and reviews, businesses can uncover valuable information to drive marketing strategies, monitor competitors, and make data-driven decisions.

Furthermore, sentiment analysis provides business managers with the ability to segment customers, tailor marketing materials, and identify competitive strategies. By leveraging sentiment analysis, businesses can enhance customer engagement, optimise marketing campaigns, and gain a competitive edge in the market. Business managers must invest in advanced sentiment analysis tools, stay updated with the latest research, and adapt their strategies to overcome language challenges and the ever-evolving nature of sentiment analysis. By doing so, businesses can harness the power of sentiment analysis to understand customer sentiments, uncover market trends, and drive business growth.

In a world where customer feedback and online interactions play a significant role in shaping brand perceptions, sentiment analysis offers businesses an opportunity to gain valuable insights and make informed decisions. By embracing sentiment analysis and its methodologies, businesses can better understand their customers, improve their products and services, and ultimately thrive in today's dynamic market landscape.

Study's Contribution

Firstly, the study streamlines the understanding of sentiment analysis for business organisations, entrepreneurs and managers who are not familiar with the vocabulary associated with computers and other technical artificial languages. It provides a comprehensive understanding of the different types of opinions, including regular and comparative opinions, explicit and implicit opinions, and subjective and objective opinions. By exploring these distinctions, the study enhances the comprehension of the complexity of sentiments expressed in text data.

Likewise, this study highlights the challenges and complexities associated with sentiment analysis, such as the influence of context, language nuances, and the need for accurate classification of subjective and objective statements. By acknowledging these challenges, the study emphasises the importance of employing advanced methodologies and tools to extract meaningful insights from unstructured data. The study also emphasises the practical applications of sentiment analysis in business contexts. It demonstrates how sentiment analysis can be utilised to track and monitor customer opinions, analyse competitor strategies, segment customers, and tailor marketing materials. These insights contribute to the existing knowledge by showcasing the value of sentiment analysis as a decision-making tool for business managers.

Limitations of the study

Further research should explore the issue of sentiment analysis and brand acceptance in greater detail by adopting a quantitative approach. The current investigation provided limited insights into the concept of sentiment analysis, and future studies could delve deeper into its application as a machine learning tool, particularly in understanding consumer sentiments. The authors restricted the scope of this study to a scoping review encompassing empirical, non-empirical, and grey literature, which may result in a potential underestimation of the qualitative aspects related to understanding consumer acceptance of brands through sentiment analysis.

Despite these limitations, the paper offers valuable insights for business organisations, entrepreneurs, managers, and operators, as well as academia and scholars. It highlights the significance of leveraging social media platforms and actively engaging with the target audience to enhance brand acceptance. By effectively utilising sentiment analysis tools, brand operators can gain a deeper understanding of consumer sentiments and align their strategies to achieve their objectives successfully.

References

Aaker, D. A. (1996). Measuring brand equity across products and markets. *California Management Review, 38(3)*, 102.

Abu Bakar, A. R., Ahmad, S. Z., & Ahmad, N. (2019). SME social media use: A study of predictive factors in the United Arab Emirates. *Global Business and Organisational Excellence, 38(5)*, 53-68.

Abualigah, L., Alfar, H. E., Shehab, M., & Hussein, A. M. (2020). Sentiment analysis in healthcare: a brief review. *Recent advances in NLP: the case of Arabic language*, 129-141.

Anshari, M., Almunawar, M. N., Lim, S. A., & Al-Mudimigh, A. (2019). Customer relationship management and big data enabled: Personalisation & customisation of services. *Applied Computing and Informatics, 15(2)*, 94-101.

Arbelles, K., Berry, P., & Theyyil, A. (2020). Electronic word-of-mouth marketing on Amazon: exploring how and to what extent Amazon reviews affect sales electronic word-of-mouth marketing on Amazon: exploring how and to what extent Amazon reviews affect sales. *The McMaster Journal of Communication, Vol. 12*, 50-79.

Barbosa, L., & Feng, J. (2010). Robust sentiment detection on Twitter from biased and noisy data. *Proceedings of the 23rd International Conference on*

Computational Linguistics: posters (pp. 36–44). Association for Computational Linguistics.

Barth, L., Kobourov, S., & Pupyrev, S. (2014). Experimental comparison of semantic word clouds in experimental comparison of semantic word clouds. In G. J., & K. J., *Experimental Algorithms* (pp. 1-17). SEA.

Bekmamedova, N., & Shanks, G. (2014). Social media analytics and business value: A theoretical framework and case study. *47th Hawaii International Conference on System Sciences (HICSS)*, (pp. 3728-3737).

Benamara, F., Chardon, B., Mathieu, Y. Y., & Popescu, V. (2011). Towards context-based subjectivity analysis. *IJCNLP*, 1180–1188.

Bhandari, M., & Rodgers, S. (2018). What does the Brand say? Effects of brand feedback to negative eWOM on Brand trust and purchase intentions. *International Journal of Advertising, Vol. 37 No. 1*, 125-141.

Castellà, Q., & Sutton, C. (2014). Word storms: Multiples of word clouds for visual comparison of documents. *Proceedings of the 23rd International Conference on the World Wide Web* (pp. 665-675). ACM.

Chakraborty, K., Bhatia, S., Bhattacharyya, S., Platos, J., Bag, R., & Hassanien, A. E. (2020). Sentiment Analysis of COVID-19 Tweets by Deep Learning Classifiers—A study to show how popularity is affecting accuracy in social media. *Applied Soft Computing*.

Chakraborty, U. (2019). The impact of source credible online reviews on purchase intention: The mediating roles of brand equity dimensions. *Journal of Research in Interactive Marketing, 13(2)*, 142-161.

Chatterjee, P. (2001). Online reviews: do consumers use them? In M. C. Gilly, & P. J. Myers-Levy, *ACR 2001 Proceedings* (pp. 129-134). Association for Consumer Research, UT.

Chaudhri, A., Saranya, S., & Dubey, S. (2021). Implementation Paper on Analyzing COVID-19 Vaccines on Twitter Dataset Using Tweepyand Text Blob. *Annals of the Romanian Society for Cell Biology, 25(3)*, 8393–8396.

Curme, C., Stanley, H. E., & Vodenska, I. (2015). Coupled network approach to predictability of financial market returns and news sentiments. *International Journal of Theoretical and Applied Finance, 18(07)*, 1550043.

Day, M. Y., & Lee, C. C. (2016). Deep learning for financial sentiment analysis on finance news providers. *In 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM) (pp. 1127-1134)*. (pp. 1127–1134). IEEE.

Deho, B. O., Agangiba, A. W., Aryeh, L. F., & Ansah, A. J. (2018). Sentiment analysis with word embedding. *2018 IEEE 7th International Conference on Adaptive*

Science & Technology (ICAST) (pp. 1-4). IEEE.

Dubey, A. D. (2020). Twitter sentiment analysis during the COVID-19 outbreak. *SSRN 3572023.*

Ebrahim, R. S. (2020). The role of trust in understanding the impact of social media marketing on brand equity and brand loyalty. *Journal of Relationship Marketing, 19(4)*, 287-308.

El Rahman, S. A., AlOtaibi, F. A., & AlShehri, W. A. (2019). Sentiment analysis of Twitter data. *2019 International Conference on Computer and Information Sciences (ICCIS)* (pp. 1-4). IEEE.

Erkan, I., & Evans, C. (2018). Social media or shopping websites? The influence of eWOM on consumers ‘ online purchase intentions. *Journal of Marketing Communications, Vol. 24 No. 6*, 617-632.

Fan, W., & Gordon, M. D. (2014). The power of social media analytics. *Communications of the ACM, 57(6)*, 74-81.

Feldman, R. (2013). Techniques and applications for sentiment analysis. *Communications of the Acm, Vol. 56 No. 4*, 82-89.

Feng, W., Yu, I., Yang, M., & Yi, M. (2021). How being envied shapes tourists' relationships with luxury brands: a dual-mediation model. *Tourism Management, (86) 1*, 104344–105113.

Ferreiro-Rosende, E., Fuentes-Moraleda, L., & Ferreiro-Rosende, R. (2021). Artists brands and museums: understanding brand identity. *Museum Management and Curatorship (14) 17*, 1–18.

Foroudi, P., Jin, Z., Gupta, S., Foroudi, M. M., & Kitchen, P. J. (2018). Perceptional components of brand equity: Configuring the Symmetrical and Asymmetrical Paths to brand loyalty and brand purchase intention. *Journal of Business Research, 89*, 462-474.

Gopi, A. P., Jyothi, R. N., Narayana, V. L., & Sandeep, K. S. (2023). Classification of tweet data based on polarity using improved RBF kernel of SVM. *International Journal of Information Technology, 15(2)*, 965-980.

Gräbner, D., Zanker, M., Fliedl, G., & Fuchs, M. (2012). *Classification of customer reviews based on sentiment analysis. In Information and communication technologies in tourism 2012.* Springer, Vienna.

Gülcan, T., & Bayram, P. (2021). Covid-19 Sürecinde Siyasal Katılım: Sosyal Medya Üzerinden Bir İçerik Analizi. *International Journal of Economics, Politics, Humanities & Social Sciences, 4(2)*, 1-11.

Guo, J., Bai, L., Yu, Z., Zhao, Z., & Wan, B. (2021). An ai-application-oriented in-class teaching evaluation model by using statistical modelling and ensemble learning. *Sensors (21)1*, 241–252.

Hajiali, M. (2020). Big data and sentiment analysis: A comprehensive and systematic literature review.

Concurrency & Computation: Practice & Experience, 32(14), 1–15.

Hasyim, R., Omar, B., Ba-Anqud, N. S., & Al-Samarraie, H. (2020). The Application of Sentiment Analysis in Tourism Research: A Brief Review. *International Journal of Business Tourism and Applied Sciences, 8(1).*, 51-60.

He, W., Wang, F. K., & Akula, V. (2017). Managing extracted knowledge from big social media data for business decision-making. *Journal of Knowledge Management, 21(2)*, 275-294.

Hendrawan, R., Suryani, E., & Oktavia, R. (2017). Evaluation of E-Commerce product reviews based on structural, metadata, and readability characteristics. *Procedia Computer Science, Vol. 124*, 280-286.

Ibrahim, N. F., & Wang, X. (2019). A text analytics approach for online retailing service improvement: Evidence from Twitter. *Decision Support Systems, 121*, 37-50.

Ikoro, V., Sharmina, M., Malik, K., & Batista-Navarro, R. (2018). Analysing sentiments expressed on Twitter by UK energy company consumers. *2018 Fifth International Conference on Social Networks Analysis, management and Security (SNAMS)* (pp. 95-98). IEEE.

Isah, H., Trundle, P., & Neagu, D. (2014). Social Media Analysis for Product Safety Using Text Mining and Sentiment Analysis. *14th UK Workshop on Computational Intelligence (UKCI).* IEEE.

Jaganadh, G. (2012). *Opinion mining and sentiment analysis.* CSI Communications.

Jayasanka, R., Madhushani, M., Marcus, E., Aberathne, I., & Premaratne, S. (2014). Sentiment analysis for social media. *International Journal of Advanced Research in Computer Science and Software Engineering, 3(7)*, 216-22.

Joshi, M., Prajapati, P., Shaikh, A., & Vala, V. (2017). A survey on Sentiment Analysis. *International Journal of Computer Applications, 163(6)*, 34-38.

Kang, Y., Cai, Z., Tan, C. W., Huang, Q., & Liu, H. (2020). Natural language processing (NLP) in management research: A literature review. *Journal of Management Analytics, 7(2)*, 139-172.

Karimi, S., & Shakery, A. (2017). A language-model-based approach for subjectivity detection. *Journal of Information Science 43(3)*, 356–377.

Kau, E., Peral, J., Gil, D., Ferr, A., Sellers, R., & Mora, H. (2019). Managing marketing Decision-making with sentiment analysis: an evaluation of the main product features using text data mining. *Sustainabiliity, Vol. 11*, 1-19.

Keller, K. L., & Brexendorf, T. O. (2019). Measuring brand equity. *Handbuch Markenführung*, 1409-1439.

Kleindienst, D., Pfleger, R., & Schoch, M. (2015). The business alignment of social media analytics. *ECIS Completed Research Papers, 103*.

Kumar, V., Choi, J. B., & Greene, M. (2017). Synergistic effects of social media and traditional marketing on brand sales: Capturing the time-varying effects. *Journal of the Academy of Marketing Science, 45*, 268-288.

Kurniawati, K., Shanks, G. G., & Bekmamedova, N. (2013). The business impact of social media analytics. *Ecis*, 48.

Lakshmi, V., Harika, K., Bavishya, H., & Harsha, C. (2017). Sentiment analysis of Twitter data. *International Research Journal of Engineering and Technology, Vol. 4 No. 2*, 2224-2227.

Levac, D., Colquhoun, H., & O'Brien, K. K. (2010). Scoping studies: advancing the methodology. *Implementation Science, 5*, 1-9.

Li, H. X., Bruce, G. L., & Gao, H. (2023). Restaurant survival prediction using customer-generated content: An aspect-based sentiment analysis of online reviews. *Tourism Management, vol. 96*, 104707.

Li, H., Chen, Q., Zhong, Z., Gong, R., & Han, G. (2022). E-word of-mouth sentiment analysis for user behaviour studies. *Information Processing & Management, 59(1)*, 102784.

Li, L., & Zhang, J. (2021). Research and analysis of an enterprise E-commerce marketing system under the big data environment. *Journal of Organisational and End User Computing (JOEUC), 33(6)*, 1-19.

Li, M., Ch'ng, E., Chong, A., & See, S. (2018). Multi-class Twitter sentiment classification with emojis. *Industrial Management and Data Systems, Vol. 118 No. 9*, 1804-1820.

Lin, C., Liaw, S., Chen, C., Pai, M., Chen, Y., Lin, C., & Chen, C. (2017). A computer-based approach for analysing consumer demands in electronic word-of-mouth. *Electronic Markets, Vol. 27 No. 3*, 225-242.

Liu, B. (2012). Sentiment analysis and opinion mining. *Synthesis Lectures on Human Language Technologies 5(1)*, 1–167.

Markovic, S., Iglesias, O., Singh, J. J., & Sierra, V. (2018). How does the perceived ethicality of corporate service brands influence loyalty and positive word-of-mouth? Analysing the roles of empathy, affective commitment, and perceived quality. *Journal of Business Ethics, 148*, 721-740.

Mayeh, M., Scheepers, R., & Valos, M. (2012). Understanding the role of social media monitoring in generating external intelligence. *Proceedings of the 23rd Australasian Conference on Information Systems* (pp. 1-10). : ACIS.

Miley, F., & Read, A. (2011). Using word clouds to develop proactive learners. *Journal of the Scholarship of Teaching and Learning, Vol. 11 No. 2*, 91-110.

Mishev, K., Gjorgjevikj, A., Vodenska, I., Chitkushev, L., Souma, W., & Trajanov, D. (2019). Forecasting corporate revenue by using deep-learning methodologies. *In 2019 International Conference on Control, Artificial Intelligence, Robotics & Optimization (ICCAIRO)* (pp. 115-120). IEEE.

Montoyo, A., Martínez-Barco, P., & Balahur, A. (2012). Subjectivity and sentiment analysis: An overview of the current state of the area and envisaged developments. *Decision Support Systems, 53(4)*, 675-679.

Mosley Jr, R. C. (2012). Social media analytics: Data mining applied to insurance Twitter posts. Casualty Actuarial Society E-Forum. *Winter (2)*, 1.

Nazir, A., Rao, Y., Wu, L., & Sun, L. (2020). Issues and challenges of aspect-based sentiment analysis: A comprehensive survey. *IEEE Transactions on Affective Computing, 13(2)*, 845-863.

Oh, H. (2016). The effect of brand class, brand awareness, and price on customer value and behavioural intentions. *Journal of Hospitality & Tourism Research, 24(2)*, 136-162.

Pant, A., Hsieh, Y., Lee, M., & Shen, C. (2014). Pointing out differences: Consumer evaluations of comparative information across product types. *Journal of Promotion Management, Vol. 20 No. 3*, 390-409.

Peters, M., Marnie, C., Tricco, A., Pollock, D., Munn, Z., Alexander, L., . . . Khalil, H. (2020). Updated methodological guidance for the conduct of scoping reviews. *JBI evidence synthesis, 18(10)*, 2119-2126.

Pina, R., & Dias, Á. (2021). The influence of brand experiences on consumer-based brand equity. *Journal of Brand Management, 28*, 99-115.

Poecze, F., Ebster, C., & Strauss, C. (2018). Social media metrics and sentiment analysis to evaluate the effectiveness of social media posts. *Procedia computer science, 130* , 660-666.

Ribarsky, W., Wang, D. X., & Dou, W. (2014). Social media analytics for competitive advantage. *Computers & Graphics, 38*, 328-331.

Ritchie, J., & Spencer, L. (1994). Qualitative data analysis for applied policy research. In A. Bryman, & R. G. Burges, *Analysing qualitative data* (pp. 173-194). London, UK: Routledge.

Ruhi, U. (2014). Social media analytics as a business intelligence practice: Current landscape & future prospects. *Journal of Internet Social Networking & Virtual Communities*.

Sarin, P., Kar, A. K., & Ilavarasan, V. P. (2021). Exploring engagement among mobile app developers–Insights from mining big data in user-generated content. *Journal of Advances in Management Research*.

Shabbir, M. Q., Khan, A. A., & Khan, S. R. (2017). Brand loyalty brand image and brand equity: the mediating role of brand awareness. *International journal of innovation and applied studies, 19(2)*, 416.

Shang, L., Xi, H., Hua, J., Tang, H., & Zhou, J. (2023). A lexicon-enhanced collaborative network for targeted financial sentiment analysis. *Information Processing & Management, 60(2)*, 103187.

Sharma, R., Morales-Arroyo, M., & Pandey, T. (2011). The emergence of electronic word-of-mouth as a marketing channel for the digital marketplace. *Journal of Information, Information Technology, and Organisations, Vol. 6*, 41-61.

Sileyew, K. J. (2019). *Research design and methodology.* Rijeka: ntechOpen.

Singh, D., Bajpai, N., & Kulshreshtha, K. (2021). The effect of brand anthropomorphism on customers' behaviour towards the Indian hypermarket brands. *Journal of Creative Communications, (16) 3*, 266–284.

Souma, W., Vodenska, I., & Aoyama, H. (2019). Enhanced news sentiment analysis using deep learning methods. *Journal of Computational Social Science, 2(1)*, 33-46.

Srivastava, A., Singh, V., & Drall, G. S. (2019). Sentiment analysis of Twitter data: A hybrid approach. *International Journal of Healthcare Information Systems and Informatics (IJHISI), 14(2)*, 1-16.

Suman, N., Gupta, P. K., & Sharma, P. (2017). Analysis of stock price flow based on social media sentiments. *2017 International Conference on Next Generation Computing and Information Systems (ICNGCIS)* (pp. 54-57). IEEE.

Sun, S., Luo, C., & Chen, J. (2017). A review of natural language processing techniques for opinion mining systems. *Information fusion, 36*, 10-25.

Sutaguna, I. N., Fardiansyah, H., Hendrayani, E., & Yusuf, M. (2023). Brand strength for Micro, Small and Medium Enterprises. *GEMILANG: Jurnal Manajemen dan Akuntansi 3(2)*, 77-86.

Tiruwa, A., Yadav, R., & Suri, P. K. (2016). An exploration of Online Brand Community (OBC) engagement and customer's intention to purchase. *Journal of Indian Business Research, 8(4)*, 295–314.

Touriki, F. E., Belhadi, A., Kamble, S., & Benkhati, I. (2022). Sustainable Business Excellence in SMEs: Opportunities and Challenges. *Sustainable Excellence in Small and Medium Sized Enterprises: Continuous Improvement Approaches that Matter*, 23-39.

Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K., Colquhoun, H., Kastner, M., . . . Straus, S. E. (2016). A scoping review on the conduct and reporting of scoping reviews. *BMC Medical Research Methodology, 16(1)*, 15.

Uzunkaya, T. (2020). Relationship between the customer expectations from websites performance and e-wom: a study on sport shoe brands. *Press academia, (7) 2*, 80–94.

Van Dinh, C., Luu, S. T., & Nguyen, A. G.-T. (2022). Detecting spam reviews on Vietnamese e-commerce websites.

Intelligent Information and Database Systems: 14th Asian Conference, ACIIDS 2022 Proceedings, Part I (pp. 595–607). Ho Chi Minh City, Vietnam: Springer.

Vriens, M., Chen, S., & Vidden, C. (2019). Mapping brand similarities: Comparing consumer online comments versus survey data. *International Journal of Marketing Research, 61*, 130–139.

Wei, Z. (2022). Impact of Organizational Brand-Building Strategies on Organizational Brand Equity: A Moderating Role of Brand-Oriented Leadership. *Frontiers in Psychology, 13*, 919054.

Yadollahi, A., Shahraki, A. G., & Zaiane, O. R. (2017). Current state of text sentiment analysis from opinion to emotion mining. *ACM Computing Surveys (CSUR), 50(2)*, 1-33.

Yazdinejad, A., Dehghantanha, A., Parizi, R. M., Hammoudeh, M., Karimipour, H., & Srivastava, G. (2022). Block hunter: Federated learning for cyber threat hunting in blockchain-based IoT networks. *IEEE Transactions on Industrial Informatics, vol. 18, no. 11*, 8356 – 8366.

Yazdinejad, A., Parizi, R. M., Dehghantanha, A., Zhang, Q., & Choo, K. K. (2020). An energy-efficient sdn controller architecture for IoT networks with blockchain-based security. *IEEE Transactions on Services Computing, vol. 13, no. 4*, 625–638.

Younis, E. (2015). Sentiment analysis and text mining for social media microblogs using open source tools: An empirical study. *International Journal of Computer Applications, 112, 5*.

Yue, L., Chen, W., Li, X., Zuo, W., & Yin, M. (2019). A survey of sentiment analysis in social media. *Knowledge and Information Systems, 60*, 617-663.

Yuliyanti, S., Djatna, T., & Sukoco, H. (2017). Sentiment mining of community development program evaluation based on social media. *TELKOMNIKA (Telecommunication Computing Electronics and Control), 15(4)*, 1858-1864.

Yuzhong, H. (2021). Students' emotional analysis on ideological and political teaching classes based on artificial intelligence and data mining. *Journal of Intelligent and Fuzzy Systems, (40) 2*, 3801–3809.

Zucco, C., Calabrese, B., Agapito, G., Guzzi, P. H., & Cannataro, M. (2020). Sentiment analysis for mining texts and social networks data: Methods and tools. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(1)*, 1333.