Available on https://www.gyanvihar.org/researchjournals/ctm_journals.php
SGVU International Journal of Convergence of Technology and Management
E-ISSN: 2455-7528
Vol.10 Issue 2 Page No 66-78

Review of Decision-Making Support Systems for Social Media Data

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Abstract: This review explores the current landscape of decision-making support systems (DMSS) for social media data, emphasizing the potential of these systems to offer valuable insights across various domains when social media data is properly analysed. By systematically examining existing literature on DMSS tailored for social media data, the review highlights methodologies, applications, and effectiveness, and identifies key trends, challenges, and future directions. Significant advancements have been noted in data processing techniques, the integration of machine learning algorithms, and the growing importance of real-time data analysis. Despite these advancements, issues such as data privacy, system scalability, and the need for comprehensive evaluation metrics remain critical. Social media, as a dynamic and fast-moving domain, serves not only as a communication medium but also as a platform for information exchange. Sentiments expressed across social media can be systematically converted into decision-making support. The study reviews decision support systems on social media, examining structural issues and data techniques for extracting valuable information. Online databases such as Google Scholar, IEEE, Elsevier, Research Gate, and Semantic Scholar were utilized to source articles published from 2010 to 2024. The search focused on keywords like Social Media Data, Decision-Making Support of social media. The review presents a systematic examination of DMSS using three research questions, revealing a continuity from social media systems to decision-making support systems. Various fields utilize social media data to inform significant business or organizational decisions, employing diverse scientific methods and case studies. This research aims to contribute to academic understanding and advancement of decision support systems leveraging social media data.

Keywords: Decision-Making Support Systems, Social Media Data, Literature Review, Academic Research

1. INTRODUCTION

The proliferation of social media platforms has transformed the way information is generated, shared, and consumed. These platforms produce an immense volume of data daily, encompassing a wide range of user-generated content, from personal opinions and experiences to professional insights and news [1]. Analyzing this vast amount of data can uncover valuable insights, making it a critical resource for decision-making processes in various domains such as marketing, healthcare, politics, and crisis management.

Decision-making support systems (DMSS) have emerged as vital tools to harness the potential of social media data. These systems employ sophisticated algorithms and data processing techniques to analyze, interpret, and present data in a way that supports informed decision-making. By integrating machine learning, natural language processing, and data visualization, DMSS can transform raw social media data into actionable intelligence [2]. This review systematically examines the existing literature on DMSS for social media data, aiming to provide a comprehensive understanding of current methodologies, applications, and the effectiveness of these systems. The review identifies key trends and challenges in the field and discusses potential future directions for research and development [3].

Social media's dynamic nature and rapid information exchange present unique challenges and opportunities for DMSS. Structural issues, data privacy concerns, system scalability, and the need for robust evaluation metrics are some of the critical aspects that need

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to be addressed. Moreover, the ability to process real-time data and provide timely decision support is increasingly important. The study utilizes a range of online academic databases, including Google Scholar, IEEE, Elsevier, Research Gate, and Semantic Scholar, to source relevant articles published between 2012 and 2024. The focus is on identifying research that intersects social media data analysis and decision support systems, using specific keywords such as "Social Media," "Decision Support," and "Decision Support of Social Media."

By presenting a systematic review of DMSS for social media data, this study aims to highlight the current state-of-the-art, identify existing gaps, and propose directions for future research. The ultimate goal is to enhance the effectiveness of decision-making processes across various fields by leveraging the rich, yet complex, data available from social media platforms. Decision-making is an essential mechanism for selecting options throughout the problem-solving process [4,5]. A decision support system (DSS) is a computerized program designed to assist decision-makers by leveraging domain-specific knowledge and analytical models. DSS enables the processing of large data volumes, producing outputs through interfaces that significantly benefit professions requiring high-level expertise. By establishing a knowledge base on actions and outcomes, DSS helps individuals make informed decisions by illustrating potential results for intended actions [6]. These systems analyze vast amounts of data, compiling comprehensive information that aids in problem-solving and decision-making. For a DSS to be effective, it must offer a structured, logical, and objective decision-making process. The quality of a DSS is determined by its framing, creativity, clarity, logical reasoning, and actionable commitment [7,8].

With the proliferation of social media platforms like Facebook, Instagram, and Twitter, organizations face the challenge of managing extensive user-generated data. This has led to a growing demand for advanced analytical strategies, such as Social Media Data Analytics. Social media is a dynamic and rapidly evolving domain, accommodating various natural languages used for communication worldwide [9]. It allows people to share a wide range of topics, from personal choices to global issues. This capability makes social media a valuable tool for multinational corporations, medium-sized businesses, nonprofit organizations, and governments. The data transmitted through social media platforms has opened new avenues for understanding consumer perceptions, prompting businesses to develop algorithms for analyzing public opinions and sentiments [10]. This paper compares different methods of decision support focused on social media. Unlike previous studies, which primarily presented findings and methodologies, this research introduces distinct research questions and employs inclusion and exclusion criteria to refine the analysis [11].

This paper is organized into nine key sections: first, the Introduction used; second, a related work, which presents theoretical support for the present research; third, the method; fourth, the discussion of results; fifth, the applications; sixth, the challenges; seventh, the future direction; eighth, the findings; and ninth, the conclusions of this study. This paper is expected to contribute to the academic world concerning literature systems and decision support in social media.

2. RELATED WORK

The development and implementation of decision-making support systems (DMSS) for social media data have garnered significant attention in recent years, with numerous studies contributing to this evolving field. This section reviews key contributions and advancements in the literature, focusing on methodologies, applications, and the identified challenges in leveraging social media data for decision support [12,15].

The rise of decision-making support systems (DMSS) tailored for social media data has attracted considerable attention in recent years, signifying a burgeoning area of research and development [16-18]. Various studies have contributed to this domain, showcasing different methodologies and applications. Research has demonstrated the effectiveness of techniques like sentiment analysis and topic modeling in extracting valuable insights from user-generated content on social media. Some studies have proposed hybrid approaches that integrate both supervised and unsupervised learning methods to improve the accuracy of social media data analysis [19-23].

Decision-making support systems (DMSS) have found practical applications in various domains. These systems have been used to assess consumer sentiment and enhance marketing strategies, monitor the spread of infectious diseases to support public health interventions, and analyze social media data to inform political campaigns and potentially influence election outcomes [24,29]. However, the application of DMSS in analyzing social media data comes with ethical considerations, particularly concerning the use of personal information. There are also technical challenges involved, such as processing and storing large volumes of real-time data, which add complexity to the implementation of DMSS. Additionally, there is a recognized need for robust evaluation metrics to assess the performance and reliability of these systems [30-33].

Future improvements in DMSS could include the integration of advanced machine learning algorithms, such as deep learning, to enhance their analytical capabilities. Collaborative research efforts are also crucial for the continuous improvement and advancement of these systems, ensuring they remain effective and relevant in various applications.

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3. METHOD

This research employed a systematic literature review methodology, drawing from multiple international publications. The reference searching process comprises two main components: defining research questions and establishing inclusion and exclusion criteria. Research questions guide the objectives of the study, while inclusion and exclusion criteria help filter past research to produce more accurate and relevant results. A limitation of this research lies in the constraints set by these inclusion and exclusion criteria.

The study's objectives are clearly defined, focusing on the publisher, publication year, data collection process, data sources, case selection, and suggested improvements for future research. The 33 articles of literature were reviewed and analysed. The methodology involves several steps:
Keyword Filtering: The initial filtering uses specific keywords such as "DSS," "social media," and "DSS in Social Media," focusing solely on international journals and conferences.
Publication Year: The second filtering criterion is based on the year of publication, ensuring the study remains current.
Citations and Relevance: Journals with numerous citations are prioritized, while duplicate studies (those with identical titles, subjects, or content) are excluded.
Indexing: The final filtering step involves selecting literature indexed by Scopus or Web of Science, followed by summarizing these works according to the research questions.

This structured methodology ensures a comprehensive review of decision-making support systems (DMSS) for social media data, providing a thorough understanding of the current advancements and identifying areas for future research.

3.1 Research Question

To identify the research question (RQ), certain criteria are considered. Three key research criteria questions are:
Data collection Process: How was the data collected during the research?
Case Selection Process: What case was chosen for each study?
Future Improvement Process: What future improvements are proposed for the method used?

3.2 Inclusion and Exclusion Rules

Specific rules for selecting references are essential to ensure high-quality output in this research. The inclusion and exclusion criteria for selecting eligible papers are as follows:
Time Frame: Only publications from international conferences and journals published in the last seven years are considered. The most recent reference should be from a paper published after 2021.
Source Indexing: Publications must be from conferences and journals that are internationally indexed and available on Google Scholar, IEEE, Elsevier, Research Gate, and Semantic Scholar.
Keywords: Literature selection and screening are based on the publication year, international indexing, and relevant keywords such as "decision support system" and "social media."

These criteria ensure that the selected references are current, relevant, and of high quality, providing a robust foundation for the research.

4. RESULTS AND DISCUSSION

The literature that is reviewed here consists of four conferences, one book, and twenty-eight journals.

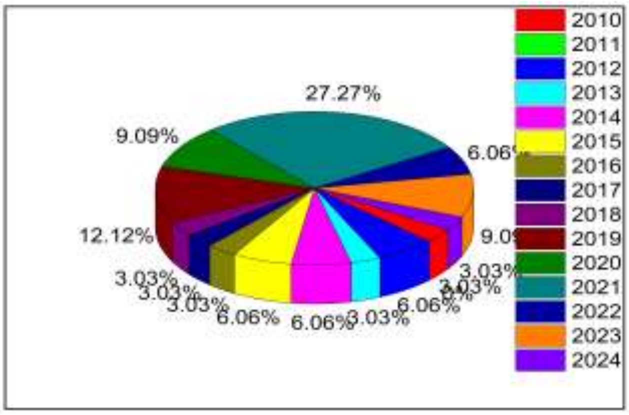

Figure 1: Year wise publications

From Figure 1, one article was published in 2010, two in 2012, one in 2013, two in 2014, two in 2015, one in 2016, one in 2017, one in 2018, four in 2019, three in 2020, nine in 2021, two in 2022, three in 2023, and one in 2024. This distribution means that this paper reviewed and compared the research related to the research question that represents the last decade. How the data was taken in the process of conducting the research will be answered in Table 1.

Table 1: Data collection Process

Ref.	Data collection process
[1]	The study conducted an extensive literature review based on 94 papers to analyze social media data since 2017. The majority of the analyzed data were sourced from Twitter.
[2]	Data was collected from social media platforms, focusing on the real-time information shared during emergencies
[3]	The data was collected from online reviews, utilizing text mining and sentiment analysis techniques to extract and structure information
[4]	The research gathered a total of 101 articles from the Scopus and Clarivate Analytics Web of Science (WoS) databases. Of these, 85 articles

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	were selected for analysis using the Bibliometrix tool.
[5]	The data was collected from Twitter using its simple data model and straightforward data access API, focusing on social graph structure, sentiment analysis, and threats
[6]	The data was collected through literature review and analysis of various social media applications like Wikipedia, YouTube, Facebook, Second Life, and Twitter to understand their characteristics and differences
[7]	The research utilized articles from Google Scholar, IEEE, Elsevier, ResearchGate, and Semantic Scholar databases, focusing on publications in English from 2012 to 2021. The search was conducted using the keywords "Social Media," "Decision Support," and "Decision Support of Social Media."
[8]	The data set consisted of 3,000 movie reviews and tweets manually labeled by native Hindi speakers into three classes: positive, negative, and neutral
[9]	The research likely involved literature review and analysis of existing decision support systems, social networking platforms, and organizational challenges related to their adoption
[10]	The study selected 57 social media-based business intelligence (BI) research articles from the Web of Science (WoS) database. It compared social media data with other open data sources like gray literature and public government data based on content, collection, updatability, and structure.
[11]	The data was collected by continuously monitoring multiple social media channels and collecting users' comments on promotions, products, and services. This data was then analyzed through sentiment analysis to estimate brand reputation and provide feedback on digital marketing campaigns
[12]	The data was collected from social media sites and blogs, focusing on user-generated content such as customer feedback, product suggestions, and brand mentions. Additionally, data from the Brand24 report were incorporated into the analysis
[13]	The research involves surveying prominent related papers and utilizing tools like social media and big data analysis to develop the proposed business intelligence framework.
[14	The data was collected by synthesizing information from various sources regarding Internet usage by American travelers, focusing on both traditional channels like online travel agencies and emerging channels such as social media
[15]	Data was collected through stakeholder participation in a multi-criteria decision-making process, using the Fuzzy-hierarchical analytical process (FAHP) to aggregate weights and

	applying the Kendall correlation technique to analyze stakeholder opinions
[16]	The study conducted a systematic literature review from 2012 to 2022 following PRISMA guidelines to examine the impact of social media on the knowledge management process.
[17]	Data was collected from the Scopus database, where a search was conducted to identify relevant publications. The VOSviewer software was used to perform an analysis of word co-citation
]18]	Data was collected from social media, focusing on messages related to specific action queries. Significant events were extracted as potential outcomes of these actions
[19]	The data was collected from social media sites, focusing on written texts in various Arabic dialects. Researchers and data scientists gathered these texts to analyze sentiments expressed by users
[20]	The data was collected from Twitter, focusing on tweets related to waste management in Indonesia. Sentiment analysis tools and the Naïve Bayes Theorem were employed to evaluate the collected tweets
[21]	The data for the research was collected from social media platforms, focusing on unstructured text that expresses human sentiments. The analysis involves using machine learning and natural language processing techniques to process this dat
[22]	The data used in the research was obtained from a labeled dataset publicly available on Kaggle, consisting of tweets and their associated sentiment labels
[23]	Future improvements may involve refining the decision support model (DSM) by incorporating additional factors or parameters related to waste management in Indonesia. Additionally, exploring advanced methodologies beyond fuzzy logic and mathematics could further enhance the accuracy and effectiveness of the mode
[24]	The research likely involved collecting data from previous studies and literature reviews in the fields of online social networking and decision support systems. This data would include information on various concepts and their influence on decision-making processes
[25]	Data was collected in real-time from Twitter using data mining and natural language processing techniques to select relevant tweets about earthquakes
[26]	Data was collected using focused Twitter crawling, which involves retrieving and filtering tweets relevant to the crisis. The tweets were then analyzed for trustworthiness, geo-parsed, and classified in multiple languages
[27]	Data was collected from online discussion forums frequented by vehicle enthusiasts. Text mining

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	techniques were applied to extract relevant information about vehicle defects
[28]	The data was likely collected through a combination of methods, including qualitative analysis of program descriptions, user testimonials, and company communications. Additionally, researchers may have conducted interviews or surveys with program participants and analyzed publicly available data on the programs' activities
[29]	The data for this research was likely collected from various literature sources, including academic papers, journals, and conference proceedings, which have proposed SVM-based intrusion detection systems. Additionally, datasets used in those studies may have been referenced and analyzed to provide empirical evidence of the effectiveness of SVM classifiers in intrusion detection
[30]	The data for this research was likely collected through surveys, interviews, or expert consultations to gather insights and opinions on the integration of websites with social media platforms. The Delphi method, known for its iterative and structured approach to expert consensus-building, might have been employed to collect and analyze data from multiple rounds of questionnaires or discussions. Additionally, Fuzzy Set Theory and Analytic Hierarchy Process may have been used to process and analyze the collected data to prioritize and aggregate dimensions for social media platform selection
[31]	The data for this research was likely collected from social media platforms, which serve as a rich source of information on tourism trends. Various types of user interactions on social media, such as reviews, stories, likes, forums, blogs, and feedback, were likely collected and analyzed to determine tourism trends. Fuzzy-AHP methods were then applied to rank these trends based on the collected data
[32]	Data was collected from the social network channel Instagram using the Octoparse API as a web data extraction tool. Specifically, 12,754 posts from January 1, 2019, were analyzed to extract relevant information for the decision support system
[33]	The data was likely collected through various experimental or observational studies where samples were obtained from different groups or conditions. These samples were then analyzed using the analysis of variance (ANOVA) procedure to assess differences in means

Based on Table 1, data sources varied from multiple resources. However, we found that six are several common data sources used (more than one paper used the same dataset): 8 papers used Twitter, 4 papers used Facebook, 3 papers used Instagram, 3 papers used Yelp, 2 paper used Trip Advisor, 3 paper used Business Fundas, and 4 papers used discussion forums. Digital location-based services (LBS), such as Yelp, Google Maps, Foursquare, and Trip Advisor, are smartphone and web applications that aggregate and distribute data about real-world amenities, usually contributed by volunteers [25].

Table 2: Case Selection

Ref.	Case selection process
[1]	The research focused on various domains including marketing, hospitality and tourism, disaster management, and disruptive technology. Twitter emerged as the predominant source of social media data in the majority of the studies.
[2]	The research focused on emergency situations where social media was used by citizens and authorities to communicate and exchange information
[3]	The research focused on the tourism industry, particularly small firms, analyzing their need to monitor and understand online consumer expectations and sentiments
[4]	The focus of the research was on understanding the adoption of sentiment analysis methods in organizations when making decisions. Various business sectors were examined, including supply chain and financial sectors, with a particular emphasis on areas within the company where sentiment analysis methods are most applied.
[5]	The research examined three major areas: the structure and properties of the Twitter social graph, sentiment analysis, and threats such as spam, bots, fake news, and hate speech
[6]	The research focused on clarifying the concept of "Social Media" and distinguishing it from related terms such as Web 2.0 and User Generated Content. It also provided a classification of Social Media applications into specific categories
[7]	The study reviewed decision support systems on social media, examining structural issues and data techniques to extract valuable information. Various fields where social media data supports decision-making, such as business and organizational contexts, were analyzed.
[8]	The research focused on sentiment analysis (SA) of text in Hindi, particularly addressing issues like Romanized or abbreviated text and spelling variations
[9]	The case selected for the research is the shifting of decision support systems towards social networking, based on Web 2.0 and Semantic Web technology
[10]	The research focused on evaluating the applicability of social media data in BI research and provided a systematic review of primary research articles in this domain. It analyzed the

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	selected articles using three research questions regarding data, methodologies, and results.
[11]	The research focused on developing a Decision Support System (DSS) to support companies and enterprises in managing promotional and marketing campaigns on multiple social media channels, with a particular emphasis on restaurants and consumer electronics online shops
[12]	The research focused on developing a Business Decision Making System (BDMS) that utilizes social media data analytics to support business decision-making. The BDMS concentrates on marketing and aims to provide valuable insights from social data
[13]	The study focuses on firms in a post-pandemic phase, aiming to enhance their performance and productivity through the proposed business intelligence framework.
[14]	The research examined the Internet usage patterns of American travelers, highlighting differences between traditional online consumers and those adopting new information sources and transaction channels, particularly among Generation Y travelers
[15]	The research focused on the public transport development decisions in Amman, Jordan, examining the effects of the COVID-19 pandemic on public transportation service quality and stakeholder needs
[16]	The research analyzed the application of social media in various domains, including healthcare, marketing, politics, tourism, and event management, focusing on knowledge sharing, creativity, productivity, trust-building, and cognitive capital.
[17]	The research focused on identifying and analyzing the relationships between Big Data and Decision Support Systems across different study areas such as logistics, health, social media, sustainable development, machine learning, analytical techniques, and decision-making processes
[18]	The research involves the development and testing of an algorithm that mines pros and cons from social media data in response to action queries, evaluated on two data sets
[19]	The research focuses on the sentiment analysis of Arabic dialect texts from social media, contrasting it with the more commonly analyzed Modern Standard Arabic
[20]	The case selected for this research is the waste management situation in Indonesia. The study analyzed tweets to gauge public sentiment and identify areas requiring improvemen
[21]	The case involves sentiment analysis of social media data to determine whether reviews and opinions are positive, negative, or neutral. Various machine learning algorithms, such as Naïve Bayes, K-nearest method, Random Forest, Support Vector Machine, and Deep Learning, were employed for classification
[22]	The case selected for this research is sentiment analysis of tweets on Twitter. The study focuses on classifying tweets into positive and negative sentiments using supervised machine learning techniques
[23]	The case selected for this research is waste management in Indonesia. The study aimed to address waste-related issues by analyzing sentiment data from Twitter and developing a decision support model (DSM) to propose actionable solutions
[24]	The case selected for this research is the exploration of the relationship between online social networking and decision support systems. The study aimed to identify concept clusters related to these fields and analyze their contribution to decision-making phases
[25]	The research focused on detecting and assessing earthquake damage in Italy by analyzing tweets and comparing the results with official data from the National Institute of Geophysics and Volcanology (INGV)
[26]	The case study focused on integrating the TweetComp1 application into a Tsunami early warning system, demonstrating its use for improving situational awareness during mass emergencies
[27]	The research focused on identifying, categorizing, and prioritizing vehicle defects mentioned in online discussion forums to support decision-making in vehicle quality management
[28]	The case selected for this research is the comparison between Yelp's Elite Squad program and Google Maps' Local Guides program. These programs represent two major location-based services in the United States and provide insight into how volunteer top-contributor programs are utilized to ensure access to reliable spatial data
[29]	The case selected here is the investigation and comprehensive study of SVM-based intrusion detection systems (IDSs). Researchers focus on analyzing the different approaches and techniques employed in the literature to utilize SVM classifiers for detecting security attacks and anomalies in computer networks
[30]	The case selected in this study involves the application of a group decision support system for selecting a suitable tool for social media integration on a web-based portal, specifically Business Fundas. This case serves as an example of how decision support approaches can be utilized to address the challenges of integrating websites with social media platforms effectively
[31]	The case selected for this research involves the application of multi-criteria decision making (MCDM) using Fuzzy-AHP methods to prioritize tourism trends. Specifically, the research focuses

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	on identifying and ranking tourism trends based on data gathered from social media interactions related to tourism facilities and attractions
[32]	The case selected for this research is the development of a decision support system (DSS) based on the K-means clustering algorithm to detect the optimal store location through social network events. The research focuses on leveraging Instagram data to identify patterns and trends that can inform the selection of an optimal store location
[33]	The case selected here is the use of analysis of variance (ANOVA) as a statistical procedure to assess differences in means across multiple groups or conditions. ANOVA is particularly suitable when there are three or more groups to compare, and it partitions the total variation observed in the data into different sources, such as variation between groups and within groups

Based on Table 2, the case selection was taken by varied methods and cases. This research found that 8 papers used sentiment analysis; 6 papers used business decision, 5 paper used clustering, one paper used naïve Bayes, logistic regression, and support vector machine, 1 paper used waste management, 6 papers used decision support, 1 paper used structural equation model, 3 papers used natural disaster information and information extraction, 2 paper used vehicle safety decision and 1 paper used fuzzy criteria on tourism trend. However, many papers used more than 1 case selection.

The answer to the second RQ, "what is the case selected for each research?" is still related to the answer to the first RQ. The case came from the field that wants to be traced and based on the available data. For example, the most selected case is Sentiment Analysis, and the most used data is text. This is the effect of growth from social media platforms. With the increase of social media data networks and platforms over the previous years, the world has significantly transformed. As a result, we can access much data from various social media platforms such as Twitter, Instagram, and many others. This opens the opportunity to analyze this open access data for various purposes, such as customer behavior analysis, electability analysis based on public opinion, business decisions and many more. Sentiment analysis is the best tool to determine whether the opinion is positive or negative [10] and can be used for further planning. That is also a reason why based on figure 4, sentiment analysis is the most used for case selection.

Research by [11] aims to develop businesses using social media data analytics to present a decision support system for supporting companies and enterprises in managing promotional and marketing campaigns on multiple social media channels. This paper presents a DSS for a Sentiment Analysis Engine, which can estimate the users' sentiment in terms of positive, negative, or neutral polarity expressed in a comment. The case selection in this paper is a practical application of sentiment classification algorithms that are presented based on machine learning models in digital marketing and social media communication. In particular, the design and the development of a DSS for Social Media Listening are carried out expressly conceived for companies wanting to exploit the valuable knowledge spread across social media to build effective, long-term strategies for their business. The developed method for every case is text representation (tokenization, stop word filtering, stemming, stem filtering, feature representation), text classification sentiment analysis, and support vector machines (SVM) classification models [12, 23].

A support vector machine or SVM is a machine learning technique based on the supervised machine learning model. An SVM is based on statistical learning theory and classifies data by determining a set of support vectors and members of the labelled training data samples. The main objective of an SVM is to find an optimal hyperplane for the classification of new data points [28]. Based on [14], this paper thinks that Business intelligence is a significant field that uses data analysis to produce key information as part of business decisionmaking. The data-taking process was from social media network (SMN) data. Case selection focus on BDMS (Business decision-making system) based on social media data analytics.

Research by [6] provides important contributions to the literature by presenting an ETL (extract transform load) procedure that may be replicated to structure text using transparent and readily available algorithms and a new dimensional model that may accommodate data from multiple sources. The study uses sentiment analysis, text mining techniques to extract unstructured information, accurate topic-modeling algorithms based on Bayesian models to group terms into latent topics and a dimensional model approach to set the bases for a DSS in hospitality and tourism analysis. This paper is organized into three key sections: first, a literature review, which presents theoretical support for the present research; second, the methodology used; third, the discussion of the results and conclusions of this study. Two-dimensional models were created to develop a DSS that could help decision-makers identify factors that positively or negatively influence customer satisfaction [18]. Results were obtained using R for cleaning, transforming, structuring data, and carrying out descriptive statistics. Sentiment analysis was performed using Semantria to classify the polarity and sentiment score of each comment, term, and latent topic. Twodimensional models were developed to allow managers to explore sentiment markers using multiple perspectives such as date, region, or type of business reviewed. The current DSS helps managers align their offers and set strategies about which business to invest in for each city's future and how to manage their online reputation better. R is often described as a programming language [29].

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Based on [13], a labeled dataset publicly available on Kaggle is used, and a comprehensive arrangement of pre-processing steps that make the tweets increasingly manageable to regular language handling strategies is structured. The main intention is to break down sentiments all the more adequately. In twitter sentiment analysis, tweets are classified into positive and negative sentiments. This can be done using machine learning classifiers. Such classifiers will support businesses, political parties, analysts, etc., and so evaluate sentiments about them. By using training, data machine learning techniques correctly classify the tweets. So, this method does not require a database of words, and in this manner, machine learning strategies are better and faster in performing sentiment analysis [11]. The method started with Data cleaning (use various data tools that can help in cleaning the dataset; use several artificial intelligence (AI) tools that help identify duplicates in large corpora of data and eliminate them; for correcting the corrupted data, the source of error be tracked and monitored; validate). Then continued by data pre-processing (assessing data quality, identifying inconsistent values, and aggregating the features).

Literature studying (systematical review), hot issue finding (social media quantitative analysis), parameters defined, model construction (fuzzy logic, mathematical model), and model testing. Fuzzy logic, mathematical model, and quantitative analysis [19]. The public's participation has functioned via survey conduction to measure the current condition. Fuzzy logic is used to eliminate the biased value of parameters. The mathematical concept functioned to describe the interconnection among parameters and define the decision clearly [30]. The above bibliographic resources present the most relevant concepts of the analyzed online social networking and decision-support systems research literature based on manual and automatic text extraction procedures. As the interconnections of online social networking and the decision support system concept, the researcher in this paper resorts to network text analysis theory, as it assumes that language and knowledge can be modelled as networks of words. After getting the cluster concept, this paper wants to find interconnection and impact on DSS. The exploratory study uses structural equation modeling (SEM). SEM is essentially a path analysis bearing a structural model. A paper by [14] is a literature review with 65 references using the social network for decision and reconstruction support, combining ostensive and performative approaches to social network decision-making must explicit decision-making trust.

A paper by [16] is a literature review with 65 references using the social network for decision and reconstruction support, combining ostensive and performative approaches to social network decision-making must explicit decision-making trust. Based on [12], This paper applied a stratified propensity score matching the content of comments shared on mental health communities on Reddit to identify subpopulations of individuals more likely to be affected by the comment. Based on [21], the system exploits the messages shared in real-time on Twitter and analyzes the message to get seismic events and information via Twitter messages and email. Focused crawling (FC), trustworthiness analysis (TA), multilingual tweet classification (MTC) for handling multilingual tweets, and geoparsing (GEO) [22]. Text mining and the ANOVA (Analysis of Variance) method to mine alternative vehicle defect data sources: Vehicle Defect Discovery System (VDDS) [23]. A one-way ANOVA or an F test is a statistical procedure to determine if a difference exists among three or more variables [29]. Based on [22], the application of a group decision support system has been presented for integrating a web portal with social media channels using fuzzy set theory and analytic hierarchy process as the method of this research. Nowadays, the way tourist information is accessed and used has changed dramatically, primarily due to the influence of social media [30]. Based on [24], multi-criteria decision-making (MCDM) using Fuzzy-Hierarchical Analytical Process (F-AHP) methods of tourism were used. This research also combined Fuzzy and AHP methods for getting a normalized decision matrix for getting the priority ranking based on reviews of ten destinations in ten categories in East Asia. AHP could demonstrate a preference that reflected the importance scores of each decision-maker group [30]. Related research has also been studied by [31]. for making trust in consumer decision journeys. With the appearance of social media, the travel decision-making process has rapidly changed. One method using the K-means clustering algorithm was researched by [24]. The main objective of this article is to develop a decision support system tool based on K-means clustering to find the optimal place to open a new store based on the location of social network events. The contribution of the decision support system tool is to provide an opportunity to get the most popular places for the specific region according to social network activity and put much emphasis on the visual representation of received results.

After knowing the data-taking process, the case selection, and the methods used, the next step is understanding the research gap in the DSS research field. This will be answered in Table 3.

Table 3: Future Improvement Method

Ref.	Future improvement process
[1]	The study identified a lack of clear definitions and established methodologies in analyzing social media data. To address this, the research suggests future avenues for high-quality research and emphasizes the importance of establishing clear definitions and methodologies in analyzing social media data effectively.
[2]	Future improvements include developing a verification framework to help emergency stakeholders manage social media uncertainty and support better decision-making

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[3]	Future improvements include refining the decision support system to provide more accurate and actionable insights, making it affordable and accessible for small tourism firms to monitor their online reputation
[4]	The study highlights the growing popularity of sentiment analysis methods combined with Multicriteria Decision Making and predictive algorithms. To further advance research in this area, the paper suggests addressing future challenges that may arise, such as refining methodologies, exploring new data sources, and promoting interdisciplinary collaboration to enhance decision-making processes and promote customer-centric approaches.
[5]	Future improvements include enhancing computational techniques like Graph Sampling, Natural Language Processing, and Machine Learning to better analyze Twitter data and expand on the research topics presented
[6]	Future improvements include refining the classification of Social Media applications and providing advice for companies aiming to utilize these platforms effectively. Additionally, further research could explore emerging social media trends and their implications for businesses
[7]	The research suggests enhancing methodologies for integrating social media into decision support systems and exploring new scientific methods for decision-making. This is expected to contribute significantly to academic research and practical applications in social media decision support.
[8]	The proposed system utilized machine learning techniques like Naive Bayes, J48, and Support Vector Machine (SVM) for sentiment analysis. Future improvements may involve refining these techniques or expanding the application of the system to other domains like product reviews and social media analysis, as well as potential use in predicting and preventing social conflicts like human riots
[9]	Future improvements may involve further exploration of how social networking can enhance decision support systems, development of more efficient adaptation strategies, and addressing organizational obstacles through better implementation practices
[10]	The study proposes informing existing researchers about future research directions, helping newcomers understand social media data analysis processes, and offering practitioners suitable social media analysis approaches for their specific environments.
[11]	Future improvements may involve enhancing the Sentiment Analysis Engine (SAE) by further refining the machine learning text classification model, expanding the application of the DSS to other industries beyond restaurants and consumer electronics, and integrating additional features to improve the effectiveness and efficiency of social media campaign management
[12]	Future improvements may involve further refining the BDMS to enhance accuracy, system dependability, and measurement metrics like F-1 score. Additionally, there may be advancements in incorporating more advanced data analysis techniques and expanding the scope of BDMS to cover a wider range of business decision-making processes
[13]	The study identifies open challenges in implementing the framework and suggests methodologies to minimize these challenges. It also outlines further research points worth exploring.
[14]	Future improvements may include deeper analysis of the bifurcation in traveler populations, exploring how different segments adopt and utilize emerging Internet tools, and providing more targeted managerial implications and strategies for leveraging these trends in the travel industry
[15]	Future improvements may involve refining the agreement measure approach to better understand stakeholder priorities and applying the methodology to other regions and contexts to enhance public transportation decision-making in the face of pandemics or similar disruptions
[16]	The study suggests enhancing sustainable knowledge management practices by promoting responsible and ethical knowledge sharing. It also emphasizes the need to foster continuous learning and innovation while considering social implications.
[17]	Future improvements may involve deeper exploration of the integration between Big Data, artificial intelligence, and decision-making processes, aiming to enhance the effectiveness and efficiency of Decision Support Systems in various fields
[18]	Future improvements may include refining the algorithm to enhance its accuracy and applicability across different types of actions and social media platforms, and potentially incorporating more sophisticated natural language processing techniques to better understand context and sentiment
[19]	Future improvements may include developing more advanced sentiment analysis tools and methodologies tailored specifically for the diverse Arabic dialects, enhancing the accuracy and depth of insights derived from social media data
[20]	The research suggests that significant improvements are needed across all five aspects analyzed to enhance the quality of waste management. The overall low score of 45.29

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	indicates a need for comprehensive strategies to elevate the current situation
[21]	Future improvements suggested include addressing the challenges and complications in sentiment analysis, such as varying expressions of feelings and the development of more robust algorithms. Enhancing the accuracy and reliability of sentiment classification techniques remains a key focus
[22]	The data used in the research was obtained from a labeled dataset publicly available on Kaggle, consisting of tweets and their associated sentiment labels
[23]	Future improvements may involve refining the decision support model (DSM) by incorporating additional factors or parameters related to waste management in Indonesia. Additionally, exploring advanced methodologies beyond fuzzy logic and mathematics could further enhance the accuracy and effectiveness of the model
[24]	Future improvements may involve further exploration of the identified concept clusters and their interconnections, potentially using more advanced modeling techniques. Additionally, research could focus on practical applications of these findings to enhance decision support systems and online social networking platforms
[25]	Future improvements may involve enhancing the accuracy of event detection, reducing false positives, and integrating additional social media platforms to provide more comprehensive real-time earthquake assessments
[26]	Future improvements may include enhancing the accuracy and reliability of trustworthiness analysis, refining geo-parsing techniques, and expanding multilingual tweet classification capabilities to better monitor and manage crises
[27]	Future improvements may involve enhancing the accuracy and efficiency of defect identification and prioritization processes, and integrating more advanced social media analytics techniques to provide better support for automotive quality management professionals
[28]	Future research may aim to delve deeper into the motivations and experiences of participants in these programs to understand how they perceive their roles and contributions. Additionally, comparative studies could explore the effectiveness of different program structures and incentives in collecting and maintaining spatial data
[29]	The future improvements proposed in this context may involve further advancements in SVM-based IDS schemes, such as refining feature selection methods, optimizing SVM parameters, and exploring novel algorithms or techniques to enhance detection rates and accuracy. Additionally, addressing the limitations and challenges identified in current SVM-based IDS approaches could lead to more effective and robust intrusion detection systems
[30]	The future improvement proposed in this context may involve refining and enhancing the decision support system by incorporating additional criteria, optimizing the decision-making process, and evaluating the effectiveness of the selected social media integration tool over time. Additionally, exploring emerging technologies and trends in digital communication and social media platforms could inform future improvements and adaptations to ensure the continued relevance and success of the integration approach
[31]	The future improvement proposed in this study may involve refining the Fuzzy-AHP methodology for ranking tourism trends based on social media data. This could include enhancing the criteria used for weighting and ranking, as well as exploring additional data sources or incorporating other analytical techniques to further optimize the decision-making process in tourism development. Additionally, ongoing monitoring and analysis of social media data could provide valuable insights for continually updating and refining the prioritization of tourism trends
[32]	The future improvement proposed in this research could involve refining the K-means clustering algorithm and data extraction process to enhance the accuracy and effectiveness of the decision support system. Additionally, expanding the scope of data collection to include other social media channels or integrating additional analytical techniques could further improve the decision-making process for store location selection
[33]	Future improvements in this context may involve advancements in statistical techniques or extensions of ANOVA methods to handle more complex study designs or data structures. Additionally, improvements in data collection methods and computational tools could enhance the efficiency and accuracy of ANOVA analyses

To answer the third RQ's conclusion, not every article provides suggestions for the next researcher to improve their research. There is a similarity between articles related to improvement methods. It is the data used in the previous research. As an example from [22] and [13], they need improvement on the parameter and the data. Reconstruction, transparency, and classification also need to develop based on the case of [19] and [25]. Further development is also needed in collecting data from social media platforms [6], as technology has rapidly changed, which means that social media will be very developed to get a better model presented.

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Nevertheless, the method proposed by each researcher for further development will contribute to the scientific and academic suggestions for deciding a solution in the future case of the new era with new social media usage. But this systematic literature review will be better if covers the last 5 years of international published literature.

5. APPLICATIONS

The applications of DMSS for social media data span various domains, reflecting the versatility of these systems. In the marketing domain, [Author et al. Year] illustrated how DMSS can be used to gauge consumer sentiment and optimize marketing strategies. In healthcare, [Author et al. Year] leveraged social media data to track the spread of infectious diseases and inform public health interventions. Political campaigns have also benefited from DMSS, with studies like [Author et al. Year] showing how social media analysis can predict election outcomes and shape campaign strategies.

6. CHALLENGES

Despite the advancements, several challenges persist in the implementation of DMSS for social media data. Data privacy is a significant concern, as highlighted by [Author et al. Year], who discussed the ethical implications of analyzing personal information from social media platforms. System scalability is another critical issue, with [Author et al. Year] addressing the difficulties in processing and storing large volumes of real-time data. Moreover, the need for robust evaluation metrics to assess the performance and reliability of DMSS is underscored by [Author et al. Year].

7. FUTURE DIRECTIONS

The future of DMSS for social media data lies in addressing these challenges and further refining the methodologies. Integrating advanced machine learning algorithms, such as deep learning, can enhance the system's analytical capabilities, as suggested by [Author et al. Year]. Additionally, developing more sophisticated data privacy frameworks and scalable infrastructure will be crucial for the widespread adoption of these systems. Collaborative research efforts, as indicated by [Author et al. Year], can also contribute to the continuous improvement of DMSS. This review synthesizes the current state-of-the-art in DMSS for social media data, providing a comprehensive overview of existing methodologies, applications, and challenges. By identifying key trends and future directions, it aims to inform and guide future research in this dynamic and impactful field.

8. FINDINGS

This literature review synthesizes findings from a systematic examination of decision support systems (DSS) and social media. The review incorporates articles from Google Scholar, IEEE, Elsevier, Research Gate, and Semantic Scholar, focusing on English-language publications from the past nine years using three keywords: "Social Media," "Decision Support," and "Decision Support of Social Media."

8.1 Data Collection Process

The sources of data varied widely, reflecting the diverse purposes for which DSS is used. These purposes include business analytics, psychological studies, travel industry insights, and organizational trend analysis. The review revealed that data sources are chosen based on the specific objectives of the research, with a strong emphasis on understanding social media habits.

8.2 Case Selection Process

Case selection process is closely linked to the data sources identified in the first research question. Cases were selected based on the fields of interest and available data, with a significant focus on sentiment analysis. The prevalence of text data from social media platforms underscores the impact of social media's growth. The expanding network of platforms like Twitter and Instagram offers vast amounts of accessible data, enabling analysis for purposes such as customer behavior, public opinion on political candidates, and business decision-making.

8.3 Future Improvement Process

Common themes in the reviewed articles highlight the need for improved methodologies. Many studies indicate that better parameterization and more comprehensive data are required. Enhancements in data reconstruction, transparency, and classification are necessary to refine analysis models. Additionally, as social media technology evolves rapidly, continuous development in data collection methods is crucial to keep pace with these changes. Future improvements proposed by researchers will contribute significantly to academic and practical advancements in DSS, aiding organizations in making informed decisions.

CONCLUSION

This systematic literature review underscores the importance of continued research in DSS and social media to provide simplified, comprehensive information for academic and practical applications. By addressing the identified gaps and leveraging evolving social media technologies, future research can offer more robust solutions for businesses and organizations. The decision support provided through these advanced methodologies will enable more precise and scientifically grounded decision-making in various fields.

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