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Review

Artificial Intelligence, Social Media and Supply Chain Management: The Way Forward

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Abstract: Supply chain management (SCM) is a complex network of multiple entities ranging from business partners to end consumers. These stakeholders frequently use social media platforms, such as Twitter and Facebook, to voice their opinions and concerns. AI-based applications, such as sentiment analysis, allow us to extract relevant information from these deliberations. We argue that the context-specific application of AI, compared to generic approaches, is more efficient in retrieving meaningful insights from social media data for SCM. We present a conceptual overview of prevalent techniques and available resources for information extraction. Subsequently, we have identified specific areas of SCM where context-aware sentiment analysis can enhance the overall efficiency.

Keywords: AI; supply chain management; social media; context-aware sentiment analysis

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1. Introduction

Social media platforms allow customers to comment about products, services, brands, or companies [1]. Customers frequently use these platforms, such as Twitter or Facebook, to share their opinions about a product or service [2]. The volume of user-generated social media data, especially customer opinions in the service and manufacturing sectors, has experienced a phenomenal rise. Social media data allow companies to gain insights into customer opinions and, subsequently, help predict consumer intentions better in the context of supply chains [3,4]. Publicly available social media data complement the traditional data sources that enterprises collect through conventional channels, such as email, calls, and surveys [2]. Relying on traditional sources of data for managing dispersed supply chain networks can have some inherent limitations. Hence, social media data is a crucial source of real-time information for efficiently managing supply chain networks. However, it is worth noting that extracting meaningful information, such as the sentiment, emotion, or opinion of stakeholders, from these social media data is not a trivial AI task due to the voluminous nature of the data and the presence of irrelevant or junk data. These noisy data 'should be verified so that good data could be picked out' to accurately extract the sentiments of the stakeholders, especially in the context of supply chains [5,6]. Hence, this paper aims to explore the relevance of context-specific applications of AI on social media data for supply chain management (hereafter SCM). To address our research objective, we explore the applications of AI for SCM. Subsequently, we probe the potential of context-aware applications of AI for extracting relevant and actionable information to improve SCM.

A plethora of papers have probed AI techniques, such as opinion mining, from the domain of natural language processing (NLP)—especially on social media data [5,7]. A few recent papers have started exploring the applications of AI for efficient SCM [8–11]. However, the literature on applying AI techniques on social media data for SCM is scant [12–14]. Hence, our paper attempts to address this gap. We considered the Google Scholar search engine to scan the extant literature on AI-based applications in the context of SCM. To identify the relevant literature, we considered the following keywords in the title of an article: 'supply chain management', 'supply chain network', 'artificial intelligence', 'AI', 'sentiment analysis', 'opinion mining', 'context-aware sentiment analysis', 'social media', 'Twitter', and 'Facebook'. However, most of these terms are generic, and Google Scholar returns a voluminous number of articles against these keywords. Hence, to identify the relevant articles, we glanced through the keywords and abstracts of these articles. For this review, we mostly considered two broad disciplines: computer science journals and proceedings and management journals—especially from the operations management area. If multiple articles made broadly similar arguments or contributions, we gave preference to articles that are highly cited. Additionally, we referred to a few theoretical or conceptual papers for SCM and sentiment analysis—especially for context-aware sentiment analysis. Finally, we identified about 85 articles, and a significant portion of these papers had been published in recent times.

The following section briefly reviews some of the initial but promising works that employed AI in SCM. This is a relatively young field of research but has gained momentum in recent times [13]. Next, we have tried to identify, based on extant literature, how AI, such as sentiment analysis, can be employed for SCM. Our brief review reveals that the supply chain is a complex network of multiple entities. Thus, based on existing literature, we tried to identify some potential supply chain applications where AI-based technologies, especially sentiment analysis and opinion mining, can create value. Sentiment analysis or opinion mining is becoming a popular tool to extract real-time and relevant information from social media deliberations [15]. However, a simplistic AI-based approach fails to extract the more delicate nuances from the social media deliberation. In other words, extracting relevant information from these social media platforms is not a trivial AI task. Thus, our paper explicitly probes the potential of context-aware sentiment analysis. To the best of our knowledge, prior studies have rarely explored the potential of context-aware sentiment analysis in the context of SCM. This is the core contribution of our paper. Figure 1 reports this core argument graphically. We explore the prevalent techniques of context extraction and, subsequently, the available tools and resources for context extraction. Our paper conceptually demonstrates the real-life implication of this proposed approach using a small number of representative tweets and argues that future research needs to probe in this direction. To sum up, the objective of this review paper is to understand how context-based applications of AI can be applied to improve the efficiency of supply chain applications.

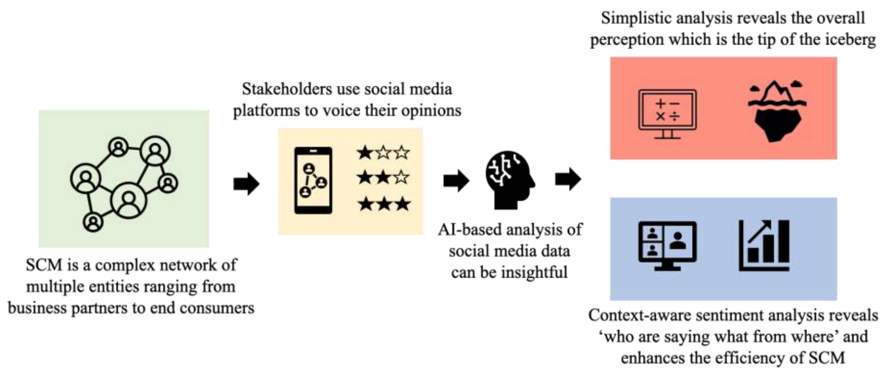

Figure 1. Application of context-aware sentiment analysis for SCM.

2. Artificial Intelligence and Supply Chain Management

The complexity of supply chains is continuously evolving in today's extremely competitive economy—especially after the COVID 19 pandemic [10]. Thus, researchers are probing whether AI-enabled supply chain applications are viable options [8,11]. Some recent works have tried to identify these trends, such as the potential of AI for SCM, through a systematic literature review [11]. Broadly, this stream of research argues 'artificial Intelligence offers a promising solution for building and promoting more resilient supply chains' and enhances the overall decision-making process [9]. Prior studies have also probed the potential of AI-enabled supply chains in specific domains, such as the pharmaceuticals, food, and drink industries [16–18]. Key findings from the influential works in this domain are presented in Table 1 at the end of this section.

In brief, a plethora of papers have probed the viability of AI-enabled supply chain applications. However, there has been no significant research on AI-enabled supply chain transformation using big data or social media data in the past [14]. Applications of AI on big data and predictive analysis on supply chain performance have not been thoroughly investigated [12]. However, big data-enabled supply chain applications are slowly gaining momentum both in academia and among practitioners.

A systematic review of 152 articles regarding the relevance of social media data for SCM reveals that 'the research interests in this area have increased dramatically within the last decade across various industries and regions' [13]. In the year 2014, the Council of Supply Chain Management Professionals (CSCMP) initiated two projects in collaboration with academia, which intended to explore the relevance of AI for logistics and SCM as follows: 'Big Data: What does it mean for Supply Chain Management?' and 'The What, How and Why of Big Data in Supply Chain Relationships: A Structure, Process, and Performance Study' [6]. Logistics professionals also started taking initiatives to implement big data-based AI strategies. The implementation of an AI-enabled supply chain is a complex process. Thus, the top management of any organization plays a crucial role in integrating big data-based AI and predictive analysis in the decision making of SCM [12]. For instance, the United Parcel Service of North America, Inc. (UPS) have invested USD one billion a year to improve its shipping business and reduce fuel and company costs. Similarly, DHL Express of Germany have launched a new trend report entitled 'Big Data in Logistics, proposing a Big Data solution to showcase the operational efficiency, customer experience, and new business models' [6].

It is worth noting that AI-enabled supply chain applications are not always about making a considerable investment. For instance, Best Buy simply uses a Twitter account to gain insights about recommendations and feedback from customers to improve their performance [19]. Employees of leading multinational enterprises from the United States, the Middle East, Europe, Asia, and Australia feel that analytics and big data-based AI positively impact the overall efficiency of SCM [20]. Broadly, practitioners have a favorable opinion about AI-enabled SCM. The literature on AI-enabled supply chains is mainly US-centric, followed by China, Taiwan, and other countries [14]. Most of these studies are published in operations research journals using data mining, optimization methods, and statistical techniques. Surprisingly, the presence of machine learning techniques or AI applications to improve sales forecasting is scant in extant literature [14,21]. We agree that social media data has some inherent limitations, such as irrelevant or junk posts by users. Thus, in place of traditional social media-based approaches, blockchain technology-based social media analytics can overcome these constraints [22]. The extant literature broadly echoed this view [17,23]. The challenge is to transform voluminous social media data into meaningful information by extracting subjective information, such as sentiment, emotion, and opinions. Subsequently, these AI-based approaches would improve the overall efficiency of the supply chain process.

The extant literature has explored the potential of social media platforms for opinion extraction and trust-building in the supply chain network [19]. The literature suggests that organizations: understand the opinions and emotions of workers from social media platforms, which management cannot access easily; create an environment to build relationships with customers by using social media platforms, such as Facebook and Twitter; integrate social media into business units, such as the marketing department. Next, the paper argues that social media platforms can foster trust and enhance communication capabilities in the supply chain [19].

Similarly, supply chain efficiency depends on mutual trust and information sharing between network entities [3]. Supply chain performance depends on 'information sharing, collaboration, trust, commitment, and volume and frequency of social media use.' [3]. Other studies have also emphasized the trust aspect [24]. This study probed the social media data of disaster relief activities because of the tragic Nepal earthquake in 2015, and considered AI-based analysis to explain 'resilience in supply chain networks for sustainability' and found that 'swift trust, public–private partnerships, and quality information sharing are important in shaping supply chain resilience and critical infrastructure resilience' [24].

Social media data can be a crucial source of knowledge discovery [19]. For instance, a simple AI-based approach, such as sentiment analysis of social media data, can help us to capture 'the happiness of completing a shipment or the frustration associated with a shipment being lost or slowed down' [19]. If supply chain disruptions are linked to an organization's reputation, then reputation analysis might help us mitigate risks. Social media data can help a company in understanding 'who is talking about a company and who appears to be listening to them' [19]. Similarly, analyzing the social network structure can help a company 'to compare the supply chain structure as it is designed with the supply chain structure as it actually emerges through agent interactions'. Social media data also helps us to understand 'who would be in the market and should there be different markets for different groups?' [19]. Hence, AI-based applications on social media data with traditional knowledge management can make SCM more efficient.

One of the initial works in this domain considered around 22,000 tweets with the hashtag #supplychain [25]. This study explored the pattern of information diffusion, prevalent topics, characteristics of Twitter users, and their opinions. In addition to the sentiment analysis, the author also performed descriptive analytics, content analytics, and network analytics. This study noted that supply chain-related tweets are 'more conversational and engaging than a random sample of tweets.' Apart from the #supplychain hashtag, this study also noted the dominance of other hashtags related to 'logistics, manufacturing, sustainability, corporate social responsibility, risk management, and IT account.' These tweets deliberated a diverse range of topics from conventional topics/hashtags, such as #logistics, #procurement, #distribution, #transportation, #inventory, and so on, to slightly counterintuitive topics/hashtags such as #humanrights, #ethics, #ClimateChange, #sustainability, #fairtrade, #humantrafficking, #equity, and so on. Interestingly, the #humanright hashtag emerged as a response to the tragic Rana Plaza accident in Bangladesh where more than 1000 workers from the textile industry died.

Moreover, tweets that contain 'timely issues and challenges' and multiple hashtags get retweeted more [25]. Consequently, the information gets widely diffused. Some of the active users in their corpus were career service organizations, followed by SCM practitioners and supply chain magazines. Most of these supply chain-related tweets contained low sentiments (except those related to specific events such as the Bangladesh garment factory collapse) because these tweets were related to a specific event—not opinionated tweets such as political or sports discourse [26,27]. However, tweets that convey dissatisfaction about 'a company's delivery service, sales performance, and ethical (or environmental) standards, and risk and disruption in the supply chain' display strong negative sentiments. Supply chain risk-related tweets not only convey strong negative emotions but also demonstrate a high diffusion rate. Similarly, another study considered two billion tweets for five years for 213 supply chain glitches from 150 publicly traded firms [28]. This study employed event-study methodology and observed that Twitter sharply reacts to supply chain glitches. Tweet volumes, mostly negative tweets, immediately go up after glitches. More importantly, 'Twitter reactions after a glitch accentuate the relationship between supply chain glitches and stock market returns, demonstrating how social media may elevate the prominence of supply chain problems' [28]. Prior studies also noted that tweet volumes and sentiments could accurately predict stock market reactions [29]. However, employing a simple lexicon-based approach ignores the context-specific polarity [21]. Generic sentiment analysis does not map the product aspect with the sentiment. For instance, a review is as follows: *The laptop's resolution is good, but the battery is problematic*. Here, we need to consider two aspects (i.e., resolution and battery) and their corresponding sentiment. Hence, to overcome the above limitations, aspect-oriented sentiment analysis can be employed in the context of SCM and demand forecasting [21].

The existing literature has tried to list down how companies can use Twitter in the context of SCM [25]. First, companies can use Twitter as a communication channel to reach out to a larger audience and engage their stakeholders. Second, companies can use the Twitter platform as a hiring tool by posting job openings and identifying promising professionals. Third, the Twitter handle of a company can help create customer demand by sharing production information and promoting offers such as coupons and discounts. Fourth, Twitter allows a company to sense the market by analyzing customers' opinions and feedback about a product, quality, and services. Finally, Twitter can mitigate supply chain-related risks by sensing disruptions and monitoring events in real-time. Moreover, during any disruption, the Twitter platform also helps in prompt information dissemination to other stakeholders involved in the process [25].

The extant literature has emphasized the need for environmental scanning 'for a firm to link the current environments (i.e., customers, suppliers, partners, and competitors) with its operations and strategic decision making in order to accommodate its business to the environments' [30]. One stream of studies conceptualized supply chain risk as the probability and impact of unexpected disruptions and events, such as 'natural disasters, political instability, terrorist attacks, equipment failure, and human error', that can potentially lead to 'operational, tactical, or strategic level failures or irregularities' [25,31]. These studies argue that accessing real-time information from social media 'about a natural disaster that happened near your manufacturing plant, information that may alter planned travel routes, or observing the path and intensity of an on-coming hurricane' can 'enable an organization to make more informed and timely decisions on how to manage or mitigate risk' [31].

From a larger perspective, the literature has also focused on supply chain risks associated with social issues. The literature has explored how AI can aid in identifying and mitigating these risks to ensure sustainability [32]. This perspective reveals that 'companies can predict various social problems including workforce safety, fuel consumptions monitoring, workforce health, security, physical condition of vehicles, unethical behavior, theft, speeding and traffic violations through big data analytics' especially in the context of an emerging economy and, subsequently, the company can take appropriate measures to mitigate these social risks [32]. However, this approach can be extended to developed as well as developing countries.

The extant literature broadly agrees that AI-based approaches to social media data allow a company to gain insight into the perception of potential and existing customers. For instance, a prior study collected Twitter data for three smartphone brands (i.e., Apple, Samsung, and Huawei) and employed sentiment and opinion analysis on their corpus to understand customers' perceptions for managing the smartphone supply chain [33]. Similarly, in the food industry context, another study collected approximately 1.3 million tweets that mentioned 'beef' and 'steak' [34]. Next, this study categorized these tweets according to their polarity. For negative tweets, 'most frequently used words associated with 'beef' and 'steak', were 'smell', 'recipe', 'deal', 'color', 'spicy', 'taste', and 'bone'. On the contrary, frequent words for positive tweets were 'fresh', 'dish', and 'taste.' Next, they employed hierarchical cluster analysis to explore the opinions of users regarding beef and steak across the globe. This allowed them to identify three dominant clusters of customer concerns as follows: the first cluster was about bone and broth—'which highlights the excess of bone fragments in the broth'; the second cluster was about jerky and smell—where customers expressed 'their annoyance with the bad smell associated with jerky'; the third cluster was about taste and deal [34].

Similarly, analysis of positive tweets allowed this study to identify two clusters as follows: the first cluster was comprised of words such as 'dish', 'win', 'gbbw' (abbreviation of Great British Beef Week), 'celebrate', 'redtractorfood', 'share', and 'hamper' (the last few keywords captured the promotional event where a company named Red Tractor had asked their 'customers to share their dish in order to win a beef hamper'); the second cluster was composed of words such as 'love', 'taste', 'best roast', and 'delicious food'. Finally, a fine-grained AI-based analysis of the social media data allowed this study to identify six significant concerns—bad flavor and unpleasant smell, traceability issues in beef products, extra fat, discoloration of beef products, hard texture, and the presence of a foreign body [34]. It is worth noting that insights from the analysis of negative tweets were more valuable than the positive tweets in designing a consumer-centric supply chain.

The literature has also probed the potential and constraints of AI-based customer analytics to improve sales forecasting in the supply chain [35]. For instance, point-of-sales data 'are integrated across multiple selling channels', allowing companies to overcome demand censuring [35]. Similarly, in-store technologies allow the probing of customer purchasing decisions. Additionally, user-generated social media data also enhance forecasting models. However, these data are voluminous, unstructured, non-repetitive, and, thus, difficult to extract relevant information from for demand forecasting. Moreover, integrating conventional sources with AI technologies is also challenging [35]. Another study explored the potential of social media data for supply chain social sustainability in the context of the freight logistics industry of Nigeria [36]. This study proposed a theoretical framework to identify critical success factors that influence social media usage by combining two streams of theories. Most importantly, this study noted that 'the integration of social media in the Nigeria freight logistics sector is still in the early stage, which signifies the slow rate of using social media'.

Table 1. AI-based approaches on social media data for SCM.

Issues	Key Takeaways
Opinion mining	Analyzing social media data, such as Facebook and Twitter, aids in investigating the opinions of stakeholders; customer analytics can improve the forecasting of sales; negative tweets are more insightful for improving SCM efficiency [19,33–35]
Relationship building	Social media platforms allow to build trust-based relationships with stakeholders; supply chain efficiency and resilience rely on mutual trust and information sharing between various network entities [3,19,24,25]
Information propagation	Social media posts, such as contextual tweets that report supply chain-related constraints or bad experience, are more interactive; tweets with multiple hashtags get retweeted more [25,28]
Reputation management	Social media, such as Twitter, spontaneously reacts to supply chain glitches; negative tweets about supply chain disruptions can have reputational concerns [19,28]
Mitigating risks	Probing social media data can reduce business/operational and social risks by sensing disruptions in real-time and ensuring supply chain sustainability [25,31,32]

To conclude, AI-enabled supply chain applications have attracted the attention of practitioners and academia in recent times. Some of the recent works have provided an exhaustive review of this stream of research [13,37,38]. Broadly, the extant literature has observed that complementing traditional sources of data, such as survey data, with publicly available data from social media platforms, such as Twitter or Facebook, enhances the performance of SCM [22]. Relying entirely on a traditional survey-based approach would be costly, and response times would be greater in the case of supply chain glitches. On the contrary, our review reveals that AI-based techniques can be employed for opinion mining, building relationships with stakeholders, understanding the nature of information propagation, managing brand or reputational perceptions, and mitigating various types of risks (refer to Table 1 for details). Most importantly, AI-based approaches allow an analysis of real-time social media data compared to traditional survey-based techniques. Interestingly, prior studies have also observed that a significant portion of social media deliberation conveys supply chain-related problems. However, negative tweets are more crucial in order to identify areas of improvement and enhance the overall efficiency of supply chains.

3. Scope of Sentiment Analysis in Supply Chain Management

We argue that the scope of sentiment analysis and opinion mining in the context of SCM can have a wide-range of applications. However, it is essential to identify potential areas of supply chain applications where opinion mining can be employed to improve the overall performance. A supply chain can be defined as 'an integrated process wherein raw materials are manufactured into final products, then delivered to customers (via distribution, retail, or both)' [34]. One stream of the supply chain literature has emphasized the overall integrative approach from procuring basic raw materials to delivering the final product to end consumers [34]. In contrast, another stream conceptualized supply chains as a network of organizations/entities that interact to coordinate the process from processing raw materials to delivering the final product/service to the end consumer [39]. It is worth noting that the 'lack of a universal definition of SCM is in part due to the way the concept of the supply chain has been developed; the concept of the supply chain has been considered from different points of view in different bodies of literature' [39]. Broadly, the supply chain can be categorized into 'four echelons (supply, manufacturing, distribution, and consumers), where each level (or echelon) of the chain may comprise numerous facilities' [34]. The complexity of a supply chain is a function of 'the number of echelons in the chain and the number of facilities in each echelon' [34]. Understanding the implicit power structure among these entities or echelons is a crucial task. However, AI-based techniques can be employed to probe the discourse of organizational communication to unravel the underlying power structure in the domain of SCM [40].

In short, SCM is a complex process, and a rich body of literature has explored various aspects of SCM. Several review papers have provided a detailed description of the same [39,41–45]. Hence, providing a holistic review of SCM is beyond the scope of our article. Moreover, social media data will not be available for all of the layers/echelons of the supply chain. For instance, the information sharing between manufacturing and distribution facilities might be an internal communication within an organization or between two network entities. We cannot expect tweet posts by stakeholders for this layer of a supply chain. Thus, the following section identifies certain crucial portions of supply chains, such as sales, inventory, and operations planning, where AI-based approaches can be applied to improve operational efficiency.

3.1. Predicting Future Demand

Predicting future demand is one of the main challenges. For instance, a crucial aspect of SCM is to tackle the 'uncertainty in demand and inaccurate customer demand forecast'—commonly known as the bullwhip effect [3]. Accurate prediction of future demand can enhance the planning efficiency. It allows businesses 'to optimize stocks, reduce costs, and increase sales, profit, and customer loyalty' [46]. Another main advantage of demand forecasting is cost savings. With accurate demand prediction, just-in-time inventory management policies can help reduce inventory levels, achieve lower inventory costs, and maintain service levels. It also helps in production management capacity planning and maximizing capital utilization. For example, additional production lines can be allocated to produce products with increasing demand and fewer production lines for dipping demands. At the same time, with accurate future demand predictions, vehicle routing planning can accomplish more efficient results with lower transportation costs [47]. The benefits of precise predictions are enormous, but the high accuracy of the future is a tremendously difficult problem due to the high complexities involved. Scholars have provided a detailed review of this domain [48]. Analysis of real-life data reveals that integrating 'different forecasting models that include time series algorithms, support vector regression model, and deep learning method' improved demand forecasting accuracy [46]. Broadly, scholars recommend AI-based techniques for anticipating demand [49].

Nevertheless, some efforts have been invested in exploring the possibility of using sentiment analysis to predict future sales [50]. Several studies have shown a high correlation between online product reviews and consumer purchase decisions [51–53]. For instance, 'social media is a source for early indicators of actual consumer demand', thus, 'social media can allow for predicting demand with greater precision than other methods' [3]. In other words, AI-based analysis of social media data can aid in 'better understanding the behaviors and preferences of the customers so that predictive models could find out the potential market and profit margin' [6]. Other studies also found statistically significant relationships of online reviews with future sales volumes [54,55]. For instance, social media data can predict success with reasonable accuracy [2]. Intuitively, a high positive sentiment count for a product will emit a strong influence on consumers to purchase the product and, thus, signify an increase in future demand; however, this might not be true, as an expression of a positive comment about a product might not reflect the intent to make a purchase decision. For instance, a person who expresses positive reviews online for a product might have already purchased the product. Hence, his positive perception might not contribute to the potential possibility for future sales. However, this logic may not be relevant to the FMCG sector—as the products generally have short lifespans. Hence, the chances of further purchases are high if a consumer is happy with the product. The massive presence of positive sentiments induces the effect of word-of-mouth (WOM), which increases product sales from other potential buyers, which creates more WOM and further sales [55]. These observations substantiate the practicality of using AI-based approaches to predict future demand. Using only sentiment data to predict future sales might have limited accuracy. However, when the results from sentiment analysis are combined with existing methods, such as autoregressive models, the accuracy of the prediction model can be improved [2].

3.2. Evaluating Product Performance

The most frequent and everyday use of AI-based sentiment analysis is the evaluation of product performance levels. For instance, AI-based approaches can track perceptions or public opinions about a specific product or service. Thus, organizations can track and monitor public opinions for products or brands through social media deliberations or product review platforms. For instance, social media data, such as tweet feeds, allow us to understand the sentiment and opinion of customers in the context of the food industry [34]. Specific aspects of the product, for example, 'taste', 'healthiness', and 'durability', can also be evaluated by specific calculated scores for each aspect, which not only identify the strengths and weakness of their products but also provide exact areas for the marketing team to play on their strengths and the R&D team to work on their weakness. Since social media data is public, a similar analysis can also be performed for competitors' products to determine relative standings [1]. Product manufacturers can tap into insights from the product performance scores instead of direct feedback from their end customers. AI-based approaches can potentially improve the effectiveness of delivering the right product to potential consumers.

3.3. Monitoring Brand Reputation

An organization's reputation is critical to its success—a good reputation is advantageous to a company. If the product quality and prices are equivalent for all competitors, customers will tend to purchase from a more reputable company or from a brand that is deemed more prestigious. Additionally, with higher reputation levels, companies can have more power to set a higher premium price for their products. Thus, maintaining a good reputation is vital for corporations due to the stiff price competition. Although reputation level is an intangible attribute, it is a critical aspect in determining a competitive advantage. With the rise of social media, the speed of information travel has been further amplified—

reflecting the high vulnerability of a company's reputation being affected via social media within a short period. Therefore, it is increasingly vital for companies to listen attentively on social media platforms; any negative discussions can potentially damage their reputation and can be detected early for immediate remedial action. AI-based approaches can help organizations in these pursuits. As we discussed previously, supply chain disruptions might be linked to the reputation of an entity. Thus, a stakeholder's reputation analysis might help us mitigate the risk associated with supply chain disruptions [19].

3.4. Evaluating Promotional Campaigns

In recent times, marketing initiatives have evolved, and companies aggressively use social media channels in addition to traditional channels. This gives organizations exposure to a large user base. More importantly, social media-based campaigns are relatively inexpensive options in comparison to traditional approaches. AI-based approaches can evaluate the effectiveness of social media marketing campaigns. Effective marketing requires multiple cycles of experimentation and optimizing, and, thus, continuous monitoring of the effects of promotional campaigns is needed to maximize the gain from marketing activities. Using AI-based analytics help in gauging the opinion of consumers, or the 'social media buzz' can be measured to reveal critical several decision results. It would also allow probing as to which channels or periods are more effective or how the marketing campaigns have affected the company's reputation or brand. As discussed earlier, a company can simply use its Twitter handle to inform its customer base about promotional campaigns such as coupons and discounts [25].

3.5. Customer Segmentation

Market segmentation is a business strategy that divides an entire market into multiple customer segments based on customer attributes. Segment-specific strategies or products can be better designed to target or differentiate specific customer groups to maximize the potential for sales. Usually, market segmentation is performed by considering demographic profiles or psychographic parameters. However, segmenting a market using manual means is challenging and can lead to inappropriate segmentations. Longitudinal data of customer-specific sentiment or opinion may provide valuable insights for performing consumer profiling and, subsequently, allows for sentimental market segmentation. AI-based analysis of customer-specific social media data can reveal untapped market segments. In other words, opinion mining can serve as an evidence-based consumer profiling, improving the accuracy of customer segmentation and allowing organizations to get to know their customers better. In this context, [19] argues that probing social media data allows us to understand 'who would be in the market, and should there be different markets for different groups?'

To sum up, this section of our paper has attempted to identify some potential areas of supply chain applications where AI-based techniques can be employed to make the process more efficient. Table 2 reports the core arguments of this section in a tabular format. We have identified five specific supply chain applications: prediction of future demands, evaluation of product performance, monitoring of organization and brand reputation, evaluation of marketing and promotion campaigns, and segmenting of the customer market. We have reviewed some of the early works in these domains or works that can be extrapolated in SCM. The next section explores why context-aware sentiment analysis can be more insightful in the context of supply chain applications.

Table 2. Scope of Sentiment analysis for SCM.

Supply Chain Applications	AI-Based Insights from Social Media Data
Predicting future demand	Social media data can reveal the market sentiment and indicate future demand
Evaluating product performance	Sentiment analysis of social media data indicates the public opinion about a specific product or service
Monitoring brand reputation	Investigating social media sentiments about a company reveals the overall brand of the company
Evaluating promotional campaigns	AI-based analysis allows to probe the overall reach and effectiveness of social media-based campaigns
Customer segmentation	Customer-level analysis reveals personal preferences, i.e., liking and disliking, for product recommendation

4. Context-Aware Sentiment Analysis

Sentiment analysis can be defined as an NLP-based approach to investigate people's sentiments and emotions toward a particular event, issue, or topic. A social media platform 'provides new tools to efficiently create and share ideas with everyone connected to the World Wide Web. Forums, blogs, social networks, and content-sharing services help people share useful information' [56,57]. Here, customers can share their opinion about a product, and potential customers can know prior users' opinions. However, this information is unstructured. Sentiment analysis can extract relevant information from this data, but the task is not trivial [4,58]. For instance, a generic word-based approach might fail to capture the implicit opinion (or apprehension) of a customer for a product, such as 'Is the Samsung Galaxy Note 7 good?' [21]. Sentiment analysis is not only a simple polarity detection task but rather an ensemble of NLP problems [59]. Generally, there are two distinct approaches to break down the text data into features—the syntactic approach or the semantic approach. Each of these approaches is based on very diverse schools of thought and is imperative to the subsequent classification step in sentiment analysis.

Syntactic features aim to capture patterns in the inherent structure of the text, which depends on specific representational rules of words defined by a language. There are several common ways of representing syntactic features, such as the standard bag-of-words (BOW), n-grams, POS tags, and negations. For syntactic-based features, the classification process is often a supervised one. On the other hand, semantic features emphasize capturing the intrinsic meaning of words as well as contextual information within the text. The most used features include sentiment orientation, appraisal groups, recognized named entities, extracted relations, and parsing. For semantic-based features, the classification process is often an unsupervised one as an external resource is required to guide how to assign quantitative values to qualitative information.

The semantic approach suggests that we need to consider the context of social media data. To capture the intrinsic meaning of social media data, we need to consider contextual information. Context information may include previous discussions, the profile of the commenters, relationships between commenters, and so on. For instance, a negative tweet about a possible delay in the delivery is relevant information. However, a negative tweet by a potential customer and a negative tweet by a business partner are not the same. The negative perception of a business partner in a supply chain network might be a more significant concern for a company than the negative perception of a not-so-significant potential customer. Contextual information, such as the profile of social media users, will tease out these finer nuances and improve our interpretation of the situation. Hence, the remaining portion of this section intends to highlight various aspects of context-aware sentiment analysis.

Contexts appear ubiquitously in almost every communication event, and the key to understanding the context is in identifying them and then utilizing the clues that contexts inherently carry. Such contextual information is often used to supplement the features of many existing AI-based applications as they provide valuable and relevant information to discern the actual situation more effectively [60–62]. Contexts can exist in various forms, and each can offer different contextual information. Understanding the various types of contexts and the opportunities arising from the usage of contextual information is critical to the study of context-aware information extraction. Such contextual information can be easily retrieved from structured data sources such as sensor data, weblog data, point-of-sale data, click-stream data, or any other spatial or temporal data. Of course, unstructured data sources, such as text, documents, pictures, and videos, also hold rich contextual information; however, extracting them into a decipherable and usable format is far more challenging as they are not organized in a pre-defined fashion. As a result, the irregularities in data organization of unstructured data require much effort to parse them into a format that a machine can understand with minimal ambiguity.

The contextual information extracted from the text can be classified into two broad categories—explicit and implicit [63]. Explicit contexts are those in which contextual information is deterministic by nature, such as time of the message, source of message, and authorship. On the other hand, implicit contexts are those in which contextual information is non-deterministic, such as semantic meaning, topic reference, objectivity, and degrees of impact. Seemingly similar implicit contexts may give very disparate contextual information. This is ordinarily found in situations where the same word(s) is/are interpreted differently under different conditions. The remaining portion of this section briefly reviews context extraction techniques, resources, and evaluation of the same. Table 3, at the end of this section, reports the critical takeaways for researchers and practitioners in a tabular format.

4.1. Context Extraction Techniques

Depending on the objective of the context extraction, different techniques can be employed to perform the extraction. These techniques are usually linguistic rules, statistical approaches, or a hybrid approach. The context extraction ranges from simple entity extraction, such as location and time, to relations extraction that requires domain knowledge. Our review has identified some of the standard context extraction techniques.

First, named entity recognition (NER), a subtask of information extraction, aims to locate and classify the elements from the corpus in pre-defined categories such as a person, organization, location, and time. NER broadly involves two tasks. The first task is to identify proper names in the text, and the second task is to classify these names into the pre-defined categories of interest. Subsequently, NER can be categorized into hand-crafted rule, machine learning-based approach, and hybrid methods [64,65]. Hand-crafted rule-based NER uses the setting of a lot of human-defined rules. These rules consist of patterns using grammatical (e.g., part of speech), syntactic (e.g., word precedence), and orthographic features (e.g., capitalization) in a combination of lexicons. Machine learning-based NER becomes a classification problem and uses statistical models to solve these problems. As the name suggests, hybrid NER combines both rule-based and machine learning-based methods. Hybrid NER utilizes the strong points from both approaches.

The second approach is probing semantic relations. These relations are the associations that exist between the meaning of words, phrases, or sentences. Some of the semantic relations are synonymy, antonymy, hyponymy, hypernym, meronymy, etc. These relations are essential to extract the relevant contexts that are required. For instance, the meronymy can extract the attributes that are part of a camera. WordNet is an online lexical database that captures most of the semantic relations [66]. However, WordNet has its limitations due to polysemy relations, a significant barrier for many systems. If a word has multiple meanings, extracting semantic relations is a challenging task. For example, the noun 'flight' has eight senses in WordNet. Consequently, WordNet might fail to determine the appropriate contextual sense. WordNet would be much more helpful if it could determine the appropriate sense of the word [66]. Despite its limitations, WordNet is still helpful for context extraction.

The third approach is analyzing dependency relations. These are grammatical relationships between the words in a sentence [67]. 'The Stanford typed dependencies representation was designed to provide a simple description of the grammatical relationships in a sentence that can easily be understood and effectively used by people without linguistic expertise who want to extract textual relations' [67]. The Stanford representation used to have about 50 grammatical relations [67]. Some of these relations are negation modifier, adjectival modifier, noun compound modifier, and possessive modifier. These relations can be used to formulate complex concepts [68].

The fourth approach is topic modeling, an unsupervised learning method that assumes each document consists of a mixture of topics, and each topic is a probability distribution over words [69]. A topic model is a document generative model that specifies a probabilistic procedure by which documents can be generated. The output of the topic modeling is a set of word clusters, and each cluster as a topic is a probability distribution over words. Latent Dirichlet Allocation (LDA) is a standard method in topic modeling. LDA defines the following generative process. Initially, for each of the documents, LDA picks a topic from its distribution of topics. Next, it samples a word from the distribution over the words associated with the chosen topic. Finally, the process gets repeated for all the words in the document [70–72]. In short, LDA uses the topic distribution differences and word co-occurrences among documents to identify the topics and word probability distribution in each topic.

The fifth approach uses conditional Markov chain models, such as conditional random fields (CRF), to extract information from semi-structured text. Such extraction includes address, last name, first name, city, and phone number. The framework combines a priori knowledge encoded as features with labeled training data to learn an efficient extraction process [73]. 'The underlying idea is that of defining a conditional probability distribution over label sequences given a particular observation sequence, rather than a joint distribution over label and observation sequences' [74]. The primary advantage of CRF over hidden Markov models is the conditional nature property. The authors of [75] proposed a general framework based on CRF to detect the contexts and answers to questions from forum threads. To sum up, AI-based context extraction techniques can be explored for managing the supply chain network, and this approach would outperform the generic approach for a challenging task such as SCM.

4.2. Context Extraction Resources

Next, we need to identify some of the available context extraction resources that can capture the relationships between the words/phrases and the patterns in the sentences. It is worth noting that these resources were employed earlier for context extraction tasks. These publicly available resources can be successfully used in the context of SCM. However, depending on the purpose of the context extraction, different resources can be used. Future research needs to probe this further.

SenticNet is a knowledge base of commonsense, and concepts are generated by applying graph-mining and multi-dimensional scaling techniques on affective commonsense knowledge collected from different sources. In SenticNet, the knowledge is represented redundantly at three levels: semantic network, matrix, and vector space. Semantics and sentics are calculated through the ensemble application of spreading activation, neural networks, and an emotion categorization model [76–78].

Similarly, ConceptNet, another publicly available semantic network, contains vast information that computers should know about the world. It is a multilingual knowledge base representing words and phrases that people use and the commonsense relationships between them. The knowledge in ConceptNet is collected from a variety of resources. These resources include crowd-sourced resources (e.g., Wiktionary and Open Mind Common Sense) [79], a game with a purpose (e.g., Verbosity and nadya.jp), and expert-created resources (e.g., WordNet and JMdict). Some of the knowledge ConceptNet includes are 'Basic knowledge' (Learn—MotivatedByGoal→Knowledge), 'Cultural knowledge' (Saxophone—UsedFor→Jazz) and 'Scientific knowledge' (Semantic role—HasContext→Linguistics).

WordNet is also a publicly available extensive lexical database of English. Nouns, verbs, adjectives, and adverbs are grouped into sets of cognitive synonyms (synsets), and each set represents a distinct concept. The synsets are interlinked using conceptual-semantic and lexical relations. The structure of WordNet is a valuable tool for computational linguistics and NLP. WordNet interlinks the senses of words together and labels the semantic relations among words. Such relations include hyperonymy, hyponymy, and ISA relation.

The Stanford Parser, another publicly available natural language parser, is a resource that considers the grammatical structure of sentences. It captures which groups of words should go together (phrases) and which are the subject or object of a verb. The parser uses language knowledge gained from hand-parsed sentences and attempts to produce the most likely analysis of the new sentences. The Stanford Parser also provides Universal Dependencies.

To sum up, context extraction can be categorized into three classes, namely, hand-crafted rule, machine-learning-based approach, and hybrid methods [65]. Rule-based approaches are usually domain-specific and difficult to generalize. These rule-based approaches can easily incorporate domain knowledge and identify the cause of errors [80]. Hence, rule-based approaches are popular in the commercial world. Machine learning-based approaches are usually a supervised categorization problem that requires a large amount of labeled data [80]. Due to data sparseness, such a large amount of labeled data is usually unavailable as it is costly and time-consuming to label the data. Hence, this approach is commercially not very popular. Finally, a hybrid method combines both rules and machine learning methods. This hybrid method requires a delicate balance between the two different approaches to achieve a desirable result. However, it is worth noting that, mostly, this approach is neither generalizable nor applicable across domains.

Table 3. Fundamentals of Context-aware Sentiment Analysis (CASA).

Building Blocks of CASA	Existing Approaches
Context extraction techniques	Named entity recognition, Analysis semantic relations, Probing dependency relations, Topic modeling, and Conditional Markov chain
Context extraction approaches	Rule-based, Machine-learning-based, and Hybrid
Context extraction resources	SenticNet, ConceptNet, WordNet, Sandford Parser
Evaluation of context-aware analysis	Accounting for content and context disagreement, Attention-based bidirectional CNN-RNN deep model

4.3. Evaluation of Context-Aware Sentiment Analysis

We also need to explore whether context-aware sentiment analysis would create value for SCM. Hence, we need to probe the evaluation and benchmarking aspects of context-aware sentiment analysis. Scholars have employed context-aware sentiment analysis on social media data [62]. This study suggests considering the influence of surrounding terms on a sentiment-bearing term (local context) and accounting for content and context disagreement between the lexicon and the domain in which it is applied (global context). This approach has outperformed the generic lexicon based (SentiWordNet) approach for three different datasets: Twitter, Digg, and Myspace.

Similarly, the literature has also explored the attention-based bidirectional CNN-RNN deep model (ABCDM) [81]. By utilizing two independent bidirectional LSTM and GRU layers, ABCDM extracts both past and future contexts by considering temporal information flow in both directions. Additionally, the attention mechanism is applied to the outputs of bidirectional layers of ABCDM to emphasize different words. Experiments conducted on five reviews and three Twitter datasets have shown that ABCDM achieves state-of-the-art results on long reviews and short tweet polarity classification. The above empirical evidence indicates that context-aware sentiment analysis can potentially achieve human-like accuracies in the long run. Thus, we feel that this context-aware approach can be extrapolated in the context of SCM for efficient information retrieval.

5. Future Research Direction: Context-Aware Sentiment Analysis for SCM

Previous sections have probed the various conceptual issues related to SCM and sentiment analysis. This leads to the intriguing question—whether implementing our proposed approach in real-life would be more insightful than traditional approaches? The scope of this review paper does not allow us to conduct full-fledged experimentation. Hence, we have extracted supply chain-related Twitter data to perform a preliminary analysis. Table 4 reports a small number of representative tweets from our corpus. We have masked the identity of social media users. Interestingly, most tweets were related to supply chain glitches, and we rarely came across positive tweets—except posts such as tweet #5. Mainly, stakeholders express their frustration or bad experience on the Twitter platform.

Simplistic polarity detection can be used to perform a binary classification of this corpus, i.e., the polarity detection column. This approach is computationally less intensive, and a lexicon-based algorithm deciphers the sentiment of a social media tweet. The brighter side of this approach is the ease of its implementation from the practical perspective. However, this lexicon-based approach may not decipher the latent or underlying meaning of a social media post. For example, it would not be able to interpret a sarcastic tweet as follows:

'Thank you (Company) for achieving the highest level of supply chain incompetency. You accept payment, take payment, give a delivery date, and fail to deliver the (product). Not only me, but my friends at (location) had a similar experience with you in the past. So, I applaud your consistency in failing again and again.'

Lexicon-based sentiment analysis would find multiple positive words/phrases: 'thank you', 'achieving', 'highest level', 'applaud', and 'consistency' and a small number of negative words: 'incompetency' and 'failing'. Thus, the lexicon-based algorithm might wrongly label this tweet either as positive or neutral. However, this tweet points out repeated bad experiences by customers for a specific company for a particular product at a specific location. A simplistic approach will fail to decipher these more delicate nuances. However, our proposed method will also extract these aspects (Table 4: Contextual information column) in addition to the sentiment (Table 4: Polarity detection column). For instance, context extraction from tweets #1, 2, and 3 reveal the non-availability of specific items in a particular location. Tweets #1 and 3 convey the perceptions of specific customer segments, namely, pet owners and older people, whereas tweet #2 shares locality level concerns. On the contrary, tweet #4 conveys the delay in delivery of a particular order of a specific customer. The company has also responded to the customer on the Twitter platform. Binary sentiment analysis will not capture this contextual information. These few sample cases from the real world demonstrate that context-aware sentiment analysis can be more insightful when compared to simplistic polarity detection.

Future research can also explore a few exciting avenues in this direction. For instance, some supply chain-related tweets are also posting images, such as tweets #2 and 3. Multi-modal sentiment analysis extracts information from both textual and visual contents, and it can outperform unimodal sentiment analysis. Accordingly, the literature has also found that the contextual integration of multimodal features is more efficient than unimodal approaches [82]. Thus, future studies can also employ context-aware sentiment analysis on multimodal social media data in the context of supply chains. Recent studies have also highlighted the relevance of efficient networks for offering low latency and high reliability during a crisis [83]. Therefore, this approach may be relevant for tackling supply chain glitches. Similarly, computationally intensive deep neural networks may not be an efficient solution for energy-constrained IoT devices. Hence, offloading these computationally intensive tasks to clouds could be an efficient approach [84]. Large logistics companies can explore these state-of-the-art approaches to make their AI-based SCM more efficient and computationally less intensive.

Table 4. Context-aware Sentiment Analysis: The Way Forward.

Sl. No.	Representative SCM-Related Tweets	Polarity Detection	Contextual Information
1	North American pet owners are struggling to track down certain foods from major retailers like Amazon, Target and PetSmart as the sector grapples with increased demand and strains on the supply chain	Negative	Location: North America Customer: Pet owners Company: Amazon, Target and PetSmart Concern: non-availability of certain items
2	@realDonaldTrump Sir, we got the toilet paper problem straightened out, however we need help with the supply chain when it comes to cleaning and disinfectant supplies. This is @Target today. @Walmart & @Walgreens still having same problems as well, here in Albuquerque, NM. 	Negative	Location: Albuquerque Company: Target, Walmart & Walgreens Concern: Non-availability of cleaning and disinfectant items
3	@Walmart is failing miserably to provide food items online, forcing older people no alternative but to get out in public. And yet they claim there's no problem with the supply chain. Then why is everything on your website 'out of stock'? *#COVID19 #CoronaVirus* 	Negative	Customer: Older people Product: Food items + screenshots of a few specific items Company: Walmart Concern: Non-availability of certain items on online platform
4	Looks like Grofers is running out of stocks. 6 days past but no sign of delivery yet. #pathetic #experience. If you guys are unable to deliver the items on time then why are you investing in ads. Better to use the money to increase tie ups and enhance #customer #experience *Response:* We regret the inconvenience caused, (masked). Your order will surely be delivered tomorrow between 6–9 a.m.	Negative	Customer: (masked) Company: Grofers Concern: Delay in delivery Future consequence: negative perception about the brand
5	Masters of logistics & Supply Chain and a zillion satisfied customers a great case study that re-defines a work culture that puts the You before Me! The #MumbaiDabawalla shares about takeaways like Passion, Commitment, Consistency and more at the #ISATownHall2018	Positive	Company: MumbaiDabawalla Perception: satisfied customers, passion, commitment, and consistency

6. Discussion

This paper has probed a number of interrelated but distinct streams of the extant literature. First, we explored the potential of social media data in the context of SCM. Social media platforms allow existing customers or business partners to share their views and opinions about SCM and allow a potential partner to gain insights before joining the supply chain network. Hence, social media platforms are acting as communication channels for information propagation. AI-based techniques, such as sentiment analysis, allow us to investigate the linguistic content of these social media posts. A negative sentiment or perception about a company on social media platforms will adversely impact its growth potential and profit margins. Thus, companies cannot rely only on traditional (and primarily periodic) sources of data collection, but they need to extract information in real-time from social media platforms. Subsequently, companies need to take prompt remedial action to address the dissatisfaction of their various stakeholders. Interestingly, negative reviews are more valuable than positive or neutral reviews. Negative comments about a supply chain application are crucial because this might need immediate attention to ensure the efficiency of the network and maintain the organization's brand and reputation. In short, AI-based analysis of social media data allows for extracting relevant and actionable information in real-time [13]. However, cyber-security could be a severe concern in a futuristic SCM, i.e., Supply Chain 4.0 [23]. Conventional social media analytics may have some limitations in terms of 'data accuracy (e.g., fake data), user privacy, data security, etc.' [22]. Hence, blockchain technology supported social media analysis can tackle these limitations [22].

Next, we briefly looked into the supply chain literature and tried to identify potential supply chain applications where AI-based analysis can create value. Probing social media data for the entire supply chain network and subsequently analyzing the whole corpus, might not be an efficient approach for the company. Social media data will be available in abundance, but mainly for a few specific supply chain applications. Based on the extant literature, we have identified five such applications: prediction of future demands, evaluation of product performance, monitoring of organization and brand reputation, evaluation of marketing and promotion campaigns, and segmenting of the customer market. Next, we probed how AI-based analysis, mostly sentiment analysis, can add value to these supply chain applications. We briefly reviewed some initial works in these domains, which offer a broad guideline for researchers and practitioners to explore these areas further.

Finally, we realize that sentiment analysis will be insightful. However, to understand the intrinsic meaning of social media data, we must go beyond conventional sentiment analysis, which ignores the context of the data. Understanding the context of the data will allow us to interpret the situation better. For instance, a fine-grained understanding of the context can reveal the orientation of social media users [26]. Hence, we have provided a brief review of context-aware sentiment analysis, existing techniques to extract the context and available resources, and algorithms to extract the context. We argue that the potential of context-aware sentiment analysis for SCM is immense [85]. Our preliminary analysis, reported in Section 5, confirms the same.

7. Conclusions

Our review reveals that AI, social media, and SCM are well-researched domains. However, there were only a handful of studies that explored AI-enabled supply chain applications in the past. Recently, researchers and corporations have started to realize the potential of the amalgamation of these domains. Supply chain applications are a complex network of multiple business entities. We argue that context-aware sentiment analysis will be more insightful than generic sentiment analysis from the perspective of managing complex supply chain networks. Table 4 highlights the same through a small number of representative tweets. It is worth noting that considering locational differences to probe location challenges and risk factors is essential for managing the supply chain networks [86]. To sum up, our paper elucidates that context-aware sentiment analysis has great potential to improve the overall efficiency of the supply chain network of logistics companies.

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